Pedestrian safety: Virtual reality simulator development and validation for analysis of alternative safety technologies

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Abstract

Rising rates of pedestrian fatalities is an urgent concern in the field of transportation. Both the National Highway Traffic Safety Administration (NHTSA) and Virginia Department of Transportation (VDOT) report gradual decreasing in pedestrian related crashes; however, they both report increasing pedestrian fatality rates. NHTSA reported a 35% increase in pedestrian fatalities nationwide between 2008 and 2017 and VDOT reported a 19% increase in pedestrian fatality rates between 2012 and 2018 in the state of Virginia.

Efforts to understand pedestrian behavior and safety have traditionally relied on real world observation methods; however, these methods are time consuming, costly, and unrealistic. With respect to motorists, driving simulators have become more sophisticated over the years and are now used as tools for understanding driver behavior and safety in realistic conditions. Efforts in creating virtual environments have been developed and tested for use in understanding non-motorized traveler behavior and safety, though, previous technologies have struggled to provide realistic and immersive environments due to the greater degree of freedom pedestrians wield over motorists.

The recent advancement of virtual reality (VR) technology has opened the door for lower cost and lower risk ways to study pedestrians' behavior, perception of safety, and acceptance of safety technology while also offering a higher degree of data resolution and level or realism compared to previous pedestrian virtual simulators. The research presented in this dissertation addresses the development of a VR simulator for studying pedestrian safety, a validation analysis of the immersive virtual environment against pedestrian behavior in the real-world environment, and a safety analysis of alternative technology treatments at the uncontrolled crossing to prove the

efficacy of using VR technology without the risks, time, and costs of real-world studies and safety analyses.

Comparisons between real world and VR pedestrian behavior showed no statistical differences in gap acceptance through the use of chi-squared analysis and crossing speed through the use of independent samples t-test at a confidence level 95%. 94% of subjects felt that they were immersed in the virtual environment and 86% felt that their experience in the virtual environment was consistent with their real-world experiences. The results from this analysis prove that the use this VR simulator is a valid approach for studying pedestrian safety at uncontrolled crossings.

Safety analysis of the unsignalized crossing within the VR environment showed beneficial correlations when incorporating alternative safety technologies through bivariate correlations. Pedestrians were able to cross the street at slower, safer speeds, rather than darting out in front of approaching vehicles, regardless of the gap size between vehicles because they were able to communicate their intent to cross with approaching vehicles. 56% of subjects reported that they felt safe crossing the road using the mobile phone application, whereas 90% of subjects felt safe crossing the road with the flashing beacons. Compared to the 26.5% of subjects who reported that they felt safe crossing the street without alternative technologies, it can be concluded that the crossing alternatives increase pedestrian safety, both behaviorally and perceptively, at the crossing.

Chapter 1: Introduction

1.1 Motivation

More than ever, non-motorized travel safety is a critical issue in transportation research. While motor vehicle occupant fatalities (adjusted for vehicle miles traveled) have generally been decreasing since the 1970s (with a small increase in 2015 and 2016), non-motorized traveler, or vulnerable road user (VRU), fatalities are increasing at alarming rates. According to National Highway Traffic Safety Administration (NHTSA), the 2016 pedestrian fatality count was the highest since 1990 (1). New solutions are needed to bolster the safety of VRUs. Efforts to understand pedestrian behavior and safety have traditionally relied on real world observation and simulation methods; however, these methods can be time consuming, costly, and unrealistic. With respect to motorists, virtual driving simulators have become more sophisticated over the years and are now used as tools for truthfully understanding driver behavior and safety in realistic conditions. Efforts in creating virtual environments have been developed and tested for use in understanding non-motorized traveler behavior and safety, though, previous technologies have struggled to provide realistic and immersive virtual environments (IVEs) due to the greater degree of freedom pedestrians wield over motorists. Within the last decade, advancements in virtual reality (VR) technology coupled with the release of commercially available VR headsets provide a platform that is immersive and offer users with the largest degree of agency over their actions in virtual environments than ever before.[1] The goal of this research is to demonstrate the feasibility of utilizing virtual reality technology as a tool for conducting real-world experimentation of pedestrian safety and behavior and to conduct a comprehensive analysis of pedestrian behavior

[1] The Oculus Rift was introduced in 2012, the HTC Vive was introduced in 2016.

using alternative infrastructure design and a prototype connected vehicle (CV) application midblock crosswalks.

Midblock crossings present a particularly vulnerable position for pedestrian safety. Conflicts arise due the reliance of nonverbal communication between users and individual choices each user must make (2)(3). Newer designs that better inform drivers of pedestrian presence and intent at midblock crosswalks have been developed and implemented, such as rapid flashing beacons (RFB). RFBs have proven to improve safety (in some circumstances) at midblock crosswalks, however, the design itself is not entirely perfect and costs a considerable amount of money to install and maintain. Connected vehicle (CV) technology provides the opportunity to increase situational awareness for all users, potentially reducing the number of vehicle-pedestrian incidents and also limit the need for installation of infrastructure such as the RFBs. Previous research conducted by the author through UVA ESE at Turner Fairbank Highway Research Center involved the development of a mobile phone application that allows pedestrians to broadcast a message directly to approaching vehicles at midblock crosswalks that notifies drivers, in-vehicle, of the pedestrian's presence and intent to cross the crosswalk (4). As this study primarily focused on the drivers' reactions and perception of the application, it is paramount to investigate how pedestrians perceive this type of messaging and whether or not they become more reliant or trusting of this information and alter their behavior at the midblock crosswalk when attempting to cross.

The challenge in testing pedestrians with these technologies in real-world environments is the control of risk that must be enforced to ensure no test subject is put in danger. By enforcing control over driver behavior when testing pedestrians, the reality of the experiment is not necessarily replicating the reality of the risks pedestrians take in everyday scenarios, hence, the results from these experiments don’t necessarily paint an accurate picture of everyday life. Test beds could be developed with these technologies in place; however, these endeavors are both time consuming and costly and the data collected from experimentation is subject to a multitude of uncontrollable environmental factors that make events almost never identical and therefore incomparable. The solution needed is a platform that not only allows for completely replicable scenarios for repeated trials, but also entirely realistic scenarios and traveler (vehicles, pedestrians, etc.) behaviors that replicate the everyday risks pedestrians face.

1.2 Research Goals

Recent studies have been taking advantage of VR to replicate realistic environmental settings at a low cost and reduced risk to the user. With VR, we can study human behaviors in settings/scenarios that we have limited or no access to (e.g., design of a new intersection that has not been built yet) or are considered high-risk environments for collecting real-life data. Additionally, these tools provide us the freedom to control and manipulate different variables of interest, which we might not have access to in real-life environments. By coupling VR tools with biometric sensors in addition to behavioral information, users’ physiological information can also be collected and analyzed. VR offers the platform needed that allows researchers to collect realistic data with complete control over the environmental factors of repeated trials.

Through the use of VR technology, the anticipated product from this research is an understanding of perceived safety and technological acceptance as it relates to pedestrians, the road environment, and CV technology. This information can be used by planners and engineers to better design technology and infrastructure for pedestrians to improve safety without the challenges of traditional methods.

The goal of this research is twofold:

I. *Pedestrian VR Simulator Validation*: Prove the feasibility of utilizing virtual reality technology as a tool for conducting real-world experimentation of pedestrian behavior. The importance of this goal is exemplified by the following:

  - Virtual reality presents the unique opportunity to test vulnerable road users in dangerous environments in a risk-free manner that would otherwise be impossible to study in real world testing, thus, eliminating the need to rely on crash data.
  - The cost and time needed for constructing actual testing environments is eliminated.
  - Multiple users can be placed in the same virtual environment to interact with each other.

II. *Safety Analysis of Alternative Pedestrian Crossing Technologies*: Understand pedestrian behavior and preferences (both stated and observed) in regards to alternative safety technology at midblock crosswalks. The importance of this goal is exemplified by the following:

  - Multiple technology and design alternatives can be developed and tested at once without having to redesign an actual intersection.
  - Pedestrian behavior can be anticipated with respect to new assistive technologies so that it may be better developed for deployment.

1.3 Research Contributions

The research presented in this dissertation contributes to the body of knowledge within transportation by establishing novel methods of understanding pedestrian safety and behavior and uses this new approach to test alternative and connected vehicle safety applications. Transportation engineers have utilized simulation methods to understand traffic patterns, safety, and driver behavior in the past. Though research has been conducted to simulate non-motorized users such as pedestrians, the technology of the past has limited our ability to create fully realistic environments for comprehensive analysis and understanding. The major contributions of this dissertation are:

- A validation analysis between real-world and virtual behavior in an IVE that is modelled on a one-to-one scale after the real-world environment
- An analysis between alternative safety measures in an IVE, proving the efficacy of VR technology in studying the safety implications of such designs without the time, cost, and safety risks of implementing these alternatives in the real world
- A development of a VR simulator and experiment methodology for testing pedestrian safety
- An expansion of the traditional methods of simulation research to include vulnerable road users (VRUs) in a fully immersible, interactable, and realistic simulation offering full range of motion
- Provides a novel approach to the development and implementation of connected and automated vehicle technology applications from the perspective of a VRU
- Provides an example of a comprehensive multimodal data simulator that provides never before collected data sources that is entirely replicable with commercially available technologies

1.4 Dissertation Overview

This dissertation is presented in seven chapters as follows:

1. Introduction

    This Chapter presents the motivations and goals of this research presented in this dissertation as wells as the overall contributions this research makes to the body of knowledge of transportation engineering and safety.

2. Literature Review

    This chapter provides a review of literature regarding pedestrian safety, simulation in transportation research, and the use of virtual reality in pedestrian research. The purpose of this chapter is to address the issues of pedestrian safety and the gaps and limitations within past pedestrian VR research. This chapter serves as the informational background for why the methodology of this dissertation was conducted the way is presented.

3. Mid-Block Crossing Connected Vehicle Application

    This chapter is dedicated to providing an overview of past research conducted by the author of this dissertation that is both relevant to the work done in this dissertation and one of the major motivations of it, as well. The mobile phone application discussed in this chapter was originally tested on drivers and, after its success in increasing driver awareness and yielding rates for the pedestrian, it was deemed imperative to test the application on pedestrians in a safe, yet realistic environment to fully understand the implications such a CV application would have on pedestrian behavior and safety. This chapter serves as a case for the need of the research presented in this dissertation to best understand VRU behavior and preferences and expedite the research process in a safe environment.

4. Methodology- Developing a Virtual Reality Pedestrian Simulator

This chapter presents the methods for developing the virtual reality pedestrian simulator in the Omni-Reality and Cognition Lab (ORCL) at the University of Virginia. Information pertaining to equipment used within the lab and reasoning for why it was chosen is provided and relates back to the literature presented in Chapter 2. Furthermore, this chapter also provides the reasoning and methodology of collecting and analyzing real-world pedestrian crossing behavior at the location of interest – the intersection of East Water Street and 1st Street South in Charlottesville, VA – and the use of this data to model traffic behavior within the IVE for experimentation.

5. Simulation Validation: Pedestrians in VR vs. Real World

    This chapter presents the analysis that validates the use of IVE and VR technologies as a platform for conducting pedestrian safety studies that are directly applicable to real-world environments. This chapter identifies the key data fields in which pedestrian crossing behavior will be assessed between the two environments and provides a detailed analysis as to the extent of which these factors influence behavior.

6. Safety Analysis of Pedestrians in VR with Alternative Technologies

    This chapter presents the analysis between pedestrian behavior within an IVE with, and without, alternative technologies designed to increase safety. The analysis in this chapter shows how IVEs and VR technology can be leveraged to understand the changes in pedestrian behavior as well as the safety impacts alternative technologies could have without the need for real-world experimentation and the limitations that come with it. This research is not only directly applicable to real-world decision making, but novel in that it offers a new approach to the development and implementation of connected and automated vehicle technology applications from the perspective of a VRU.

7. Conclusions

This chapter re-addresses the goals of this dissertation and how the analyses meet these goals to contribute to the body of knowledge of VRU research. This section further addresses the contributions this dissertation makes to the development of novel methods for studying VRU behaviors. Lastly, this chapter provides insight into future work to be conducted with the findings of the experiment described in this dissertation.

Chapter 2: Literature Review

2.1 Introduction

While current designs have aided pedestrians in crossing roadways at mid-block crossings, conflicts still arise due to the confusion these designs can cause between pedestrians and motor vehicles (5). Mid-block crosswalks are dangerous for both pedestrians and drivers because communication between the pedestrian and driver is non-verbal and each individual pedestrian decides then it is safe to cross (6). These instances are increased when a designated mid-block crossing is installed at the crossing of a greenway with a roadway due to the higher volume of pedestrians and cyclists crossing. Sometimes these mid-block crossings are across roadways where mid-block crossings are uncommon or unexpected, thus exposing users to an uncomfortable environment.

2.2 The Dangers of Mid-Block Crosswalks

Unsignalized mid-block crosswalks pose a unique and confusing scenario for all roadways users as driver and pedestrian communication, or the lack thereof, is paramount in understanding the safety of these designs. In the National Highway Traffic Safety Administration (NHTSA) 2017 annual report released in 2019, pedestrian fatalities increased by 35% over the ten-year span from 2008 through 2017 (7). Furthermore, this NHTSA report states that the percentage of pedestrian fatalities of total fatalities in traffic crashes each year increased over this same ten-year span from 12% in 2008 to 16% in 2017 and that 73% of these fatalities did not occur at intersections (7).

With respect to the state that this experiment was conducted, 13.2% of total traffic fatalities were pedestrians in Virginia (7). The Virginia Department of Transportation's (VDOT) Pedestrian Safety Action Plan released in May of 2018 states that 51% of pedestrian injury crashes and 66%

of pedestrian fatal crashes occurred at mid-block crossings (8). This report also showed that Northern Virginia, where the W&OD and Mt Vernon Trails are located, had the second highest percent of pedestrian fatal crashes in Virginia over the years of 2012-2016 and the highest percent of pedestrian injury crashes in all of the state (8). Furthermore, the report states that 71% of pedestrian fatal crashes occurred in dark or unlit conditions (8). In the Virginia Pedestrian Crash Assessment published by VDOT representing an analysis between the years of 2012 and 2016, it was discovered that pedestrian crashes accounted for 1.4% of all reported traffic crashes, but accounted for 12.5% of all traffic fatalities (9). Loudon County, the City of Alexandria, Fairfax County, and Arlington County all ranked within the top ten cities and counties for pedestrian injury and fatal crashes (9).

It would feel appropriate, then, to implement a form of control of pedestrians at these mid-block crossings. A 2017 study conducted by Coeugnet et.al. studied the effectiveness of a vibrotactile wristband older pedestrian crossing behavior in a simulated environment, alerting the pedestrian as whether they were making a safe crossing decision. Results indicated that older pedestrians responded in accordance with the wristband 51.6% of the time, however, simulated collisions did not fall to zero (10). A study conducted by Zhuang and Wu also found that pedestrians have poor crossing behavior at controlled pedestrian crossings, often overestimating their ability to cross controlled intersections with countdown timers (11). New timers with required crossing speeds reduced risky crossing behaviors in pedestrians, but did not altogether prevent them (11). While these studies reduced risky crossing behaviors, they did not mitigate the unpredictability of pedestrian behavior at crosswalks. Furthermore, Zhai et. al. found in a 2019 study that the effects of jaywalking and risky driving behavior on pedestrian crash severity were most prevalent under rainy conditions (12).

In order to attempt to combat the unpredictability of pedestrians, the City of St. Louis rewrote their laws requiring all trail users to stop and yield to vehicles at trail-roadway intersections. St. Louis deemed that trail-roadway intersections were not in fact intersections, but simply trail crossings. Thus, in order to control pedestrians at such crossings, St. Louis removed all striping at these crossings and installed stop signs and warning messages along their trails, indicating that it is state law that all trail users stop and yield to vehicles (13)(14). Ultimately, pedestrians operated as usual, with some obeying the signage posted and others ignoring these warning and stop signs and crossing with the assumption that motorists will yield to them as the new state law stated.

A similar case can be seen in Virginia at identical intersection types along the vast network of greenways in Northern Virginia. There are stop signs and warning messages along the trails at intersections with roadways, yet there is still some confusion at such crossings. Whether it be pedestrians ignoring the signs and walking into the roadways with the assumption that they have the right of way or pedestrians stopping as the signage demands, yielding to vehicles, only to encounter vehicles yielding at the crosswalk to pedestrian leaving pedestrians to cross with the assumption that vehicles in adjacent lanes will do the same. Such uncontrolled mid-block crossings foster unpredictable and unsafe situations, leaving all of the decision making at these intersections in the hands of each individual, thus increasing the potential of possible incidents.

2.3 Simulation in Transportation Research

Modelling helps transportation engineers better understand, design, and manage our roadways to make them safer and more efficient for all users. As new technology is developed, new methods and data can be studied to make better informed decisions and designs to further increase safety and efficiency. Simulation is one of the best ways we can, as transportation engineers, understand all of the factors that influence user behavior and safety and have been used extensively in previous research. Traditionally, transportation engineers have taken a vehicle-centric approach to understanding roadway safety through use of simulation models on a micro and macroscopic level and driving simulators on an individual level. As simulation-based approaches evermore become the standard for managing and designing for vehicles, the same approach could be leveraged for VRUs.

2.3.1 Traffic Simulation Modelling

Transportation engineers have used simulation methods for modelling and analyzing traffic operations under different treatments to better plan for and manage future traffic demand. Simulation modelling (both micro and macroscopic) has proven a successful approach to managing traffic conditions and has thus been developed to be used as the industry standard for real-time traffic management (15). Furthermore, traffic simulation has also been used for increasing safety of roadways. A 2020 review of literature shows that current trends in simulation modelling aim to predict vehicle crashes, whereas traditional methods have focused primarily on implementing traffic control (16). Additionally, with the development and implementation of CV and AV technology, simulation-based approaches are being leveraged to understand the implications these technologies will have on operations and safety due to the lack of empirical data (17). Increasingly, proactive simulation-based modelling approaches are becoming the standard for understanding and managing roadway operations and safety. Further clarity on the implications of new technologies, designs, and operations is needed on the individual level as well for understanding public acceptance and understanding of new treatments, leading to the use of virtual simulation.

2.3.2 Driving Simulation

Virtual driving simulator methods help understand the perceptions, behaviors, and preferences of individuals with respect to new roadway designs, technologies, and operations. The outcomes of these studies help to better predict real-world operations in traffic modelling, understand the implications new treatments may have on safety, and educate users on the operations of new treatments. Past research has validated the use of driving simulators for studying driver behavior so that the results of these studies can be taken at face value (18)(19). Due to the validity of simulator results, driving simulators have since been used for behavior studies, driver education and training, infrastructure design, medicine, ergonomics, and intelligent transportation systems development (20)(21). Due to the validity and the removal of risk from real-world danger, virtual driving simulators have become the standard for understanding driver behavior and preference, thus, it is no surprise that this approach could be leveraged to study arguably the roads most vulnerable user – pedestrians.

2.4 Virtual Reality Simulation

2.4.1 The Use of VR Simulation in Understanding Pedestrian Behavior

The use of virtual reality in pedestrian studies cover a wide range of topics from educating children on safe road crossing behavior to understanding the perception of walking speed in virtual space. Not only have the topics of research varied over the years, so, too, has the technology. Many recent studies involve the use of HMDs, as opposed to the stationary single or multiscreen platforms used in early simulator iterations (with the exception of the earliest studies which utilized older, inferior HMD technology).

Simpson et al. conducted a study in 2002 investigating road crossing behavior of children and young adults with respect to collisions, near misses, cautious crossings, crossing time, and gap acceptance, utilizing previous generation HMD technology (22). Results of the study suggested an increased level of immersion as compared to prior studies involving display monitors. The study also implied higher collision rates in the virtual environment (as compared to real-world data) may be a result of subjects' riskier behavior in a risk-free environment. In 2005, Banton et al. investigated the perceptions of subjects' walking speeds in virtual reality, also using a HMD to validate the usefulness of virtual technology for pedestrian research (23). The researchers found that subjects' misperceptions were often due to a lack of sensory cues, largely because of the HMD's restrictions in peripheral vision and a lack of stereoscopic imaging. These early studies employing the use of HMDs were limited by low-resolution, 640 x 480 pixel displays for each eye, synoptic imaging instead of stereoscopic imaging, and a diagonal 48-52 degree field of vision, compared to the natural human field of vision of 180 degrees. The authors of both the Simpson et al. and Banton et al. papers believed that these factors impacted subject behavior due these limitations on perception of space in the virtual environment (22)(23), stating that stereoscopic imaging was too difficult to perform, so synoptic imagery was used instead. Furthermore, the headsets operated on lower resolutions and frame rates, which created blurry images and jittery frames.

For approximately ten years after these early iterations of HMDs were used in pedestrian studies, multiscreen virtual environments dominated the pedestrian simulator literature. Multiscreen and projection-based technologies were used for a broad range of studies including designing and testing educational programs, understanding pedestrian behavior, and testing new roadway designs. Studies using multiscreen displays mitigated some of the early issues with HMD technology by providing a much larger field of vision, eliminating the restrictions of cable management with headsets, and reducing visual distortions and movement jitter due to the computational power required for HMD technology use. In 2008, Schwebel et al. sought to validate the use of virtual reality as a preventative tool to improve safe street-crossing behavior to limit child pedestrian injuries (24). The study implemented a multiscreen environment where subjects would stand in front of the virtual environment and observe the associated scenarios. After the crossings were completed, participants briefly reported on the realism of the VR environment and any discomfort they experienced. Three main measures were collected in all trials to assess safety: average gap size available, average wait time over cars passed, and average start delay. Overall, adults rated the VR environment as "quite realistic" and children rated it slightly lower. In 2009, Neider et al. used a similar virtual multiscreen approach to test how divided attention affected pedestrian behavior when crossing a busy street (25). The simulator involved subjects walking on a treadmill while looking at a stationary multiscreen display. The study found that successful crossing rates differed between undistracted and distracted users; however, the study found an uncharacteristically low percentage of successful crossings. The authors pointed out that many of the crossing failures were due to the testing time expiring while the pedestrians were distracted, as many of them were over-cautious and did not cross within the maximum 30 second time window. However, authors believed that the low rate of successful crossings does not suggest that the simulated environment or task was unduly hazardous, but rather a consequence of the test design.

In 2010, Schwebel et al. conducted another study aimed to study the effectiveness of virtual reality as a way to teach safe street-crossing behavior to children (ages 7-8) utilizing the same simulator validated in their 2008 study (26). Four groups were formed for testing: one group took part in six sessions of training in an immersive virtual reality environment, the second group took part in six sessions of training through widely-used computer video-based programs, the third group took part in individualized personal training at real-world streetside locations, and the final group served as a no-training control group. All groups had their behavior tested prior to training, after training, and at a six-month follow-up assessment. As a follow-up study in 2015, Schwebel et al. conducted a before and after within-subjects trial of training children in pedestrian safety using a semi-mobile, semi-immersive virtual pedestrian environment placed at schools and community centers (27). The findings of this study suggested that virtual reality environments placed in community centers had the potential to teach children to be safer pedestrians. To further understand the effectiveness of virtual reality as a training tool, Shen et al. conducted another study with the same simulator from the Schwebel studies, examining the relationship between stated temperamental fear and risky behavior in children (28). Results indicated some correlation between fear and crossing behavior and suggested that future research should explore how factors such as fear could influence the effectiveness of incident prevention programs.

The Schwebel simulator was also used in 2013 by Byington et al. to investigate whether young adult pedestrian safety is compromised when subjects crossed a street while using a cell phone (29). Results indicated differences in crossing behavior in subjects with generally riskier behavior being observed in instances when subjects were distracted with their phones. Schwebel et al. also conducted a similar experiment in 2012 that investigated the influence of conversing on the phone, texting, and listening to music on pedestrian crossing behavior (30). The experiment consisted of 138 college students crossing an interactive, semi-immersive virtual street displayed on three monitors arranged in a semicircle in front of the student. In 2016, Rahimian et al.

conducted an experiment with a large-screen immersive virtual environment, similar to a CAVE system, to evaluate how texting pedestrians respond to traffic alerts delivered via their cell phone (31). Results of this study suggested that vehicle-to-pedestrian communications could help mitigate collisions between pedestrians and vehicles during street crossings. In 2017, Schwebel et al. conducted another study with their multiscreen virtual environment by testing pedestrian exposure to texting while crossing an intersection (32). Individuals exposed to texting within a simulated pedestrian environment reported changes in their intentions to cross streets and in perceived vulnerability to risk while crossing streets.

Through the use of their multiscreen display system, the Schwebel studies demonstrated the effectiveness of virtual reality for research in pedestrian behavior and training. A few later studies used newer display technology, particularly the cave virtual reality (CAVE) system. Tzanavari et al. conducted a 2015 study that tested the efficacy of virtual reality in improving pedestrian crossing behavior (33). This study only tested training in a CAVE environment (with no comparison to other training methods) and was focused specifically on six children with Autism Spectrum Disorders (ASD) ranging from 8 to11 years old. This experiment consisted of a four day training period to investigate whether the CAVE VR environment could be used as a tool to improve crossing behavior. Based on results describing each participant's correct steps per day per trial, all children demonstrated progress and were able to complete the task with no mistakes by the end of the fourth day. Furthermore, all children were able to demonstrate competency in crossing the street in the real environment at the post-training evaluation. In 2017, another study by Jiang et al. also used a CAVE system to examine how people behave at road crossings (34). In this study, pedestrians attempted to cross a crosswalk in the presence of another pedestrian whose behavior varied between safe and risky. This study employed the use of two different partner pedestrians - one programmed into the virtual environment and one researcher walking alongside the test subject- in different trials. Results indicated that subjects preferred crossing with a partner, in particular their human partner over the virtual one, regardless of the riskiness of the partner's behavior.

While multiscreen and CAVE projections were easier to use, some studies reported possible implications of these technologies' decreased levels of immersion and subsequent impacts on subject behavior (25). Few studies provided validations of their testing methodologies and technology; however, those that did, such as the 2008 Schwebel et al. study, continued to use their simulator for years in various research studies (24). During the years when the CAVE system was becoming popular in pedestrian research, the HTC Vive and Oculus Rift were released. These commercially available HMDs made the use of VR technology for research more cost-effective than ever before, and marked a resurgence in the use of HMDs in recent pedestrian simulator studies. These more recent studies involving the use of HMD technology primarily relied on the Oculus Rift or HTC Vive, both having 1080 x 1200 pixels per eye at a possible refresh rate of 90 Hz and a field of vision of 110 diagonal degrees (35). These recent studies using HMD validate the use of virtual reality environments as a meaningful tool to study pedestrian and bicyclist safety and behavior with some limitations in perceptions of walking speed, motion sickness, and cable management.

In 2018, Farooq et al. presented their VIRE (Virtual Immersive Reality Environment) system, which is capable of developing highly realistic, immersive, and interactive choice scenarios via a HMD (36). Their investigation focused on pedestrian preferences related to autonomous vehicles and associated infrastructure changes on urban streets. Also in 2018, Deb et al. investigated what external features on autonomous vehicles could help pedestrians best understand the intentions of a vehicle at a crosswalk (37)(38). The study was conducted using a HMD and yielded positive results showing that pedestrians' receptivity of autonomous vehicles increased with the inclusion of external features. Bhagavathula et al. conducted a study in 2018 utilizing HMDs to understand how pedestrian perception and behavior in virtual reality compared to those of real world experiences (39). In this study, subjects experienced the same environment and scenarios in both virtual and real environments. Analysis between the two settings found that there was little difference in pedestrian behavior and perception aside from perception of walking speed. Also in the same year, Iryo-Asano et al. conducted a similar comparison study between real-world and virtual environments with HMDs, examining the applicability of VR to pedestrian perception and behavior analysis (40). Results indicated that the field of view of the display may have implications on how pedestrians interpret their surroundings, possibly leading to changes in behavior.

Virtual reality has been used for wide ranging applications in pedestrian studies: understanding pedestrian behavior, validating immersion in simulated environments, and as a teaching tool. The technology used in pedestrian studies has followed a cyclical trend with early research utilizing HMD technology before abandoning it, largely due to technical limitations, for multiscreen displays, only for later studies to return to the use of HMD technology once it was more commercially available. These shifts in technology and purpose of research mark a transition to more multidisciplinary approaches in pedestrian studies, incorporating psychological, physiological, and computer science elements to better understand the implications that virtual reality has on pedestrian behavior and research.

2.4.2 Gaps in Research

Though VR has been used in the past for VRU research, the technology has improved over the years providing opportunities for better research. The last two decades have seen research focusing on the dangers VRUs face and how countermeasures influence safety - elements such as walking speed, gap acceptance, analysis of risky behavior, stated preference data, visual or auditory warning effectiveness, speeds, steering, and resistance have all been the commonly discussed in VRU research (25)(37). Trends in the use of VR technology in VRU research indicate that commercially available technology appears to drive the method of immersion simulators are based on, thus as more immersive and efficient virtual reality technology became commercially available, research with bicycle and pedestrian simulators began to more readily utilize this technology as a means of understanding human behavior.

Arguably the biggest gap in IVE VRU research is the lack of standard practice methods for cross-comparing studies - it is difficult to draw conclusions relating to technology effectiveness between a simulator using screens and another using a HMD because validation studies are not consistent between simulators and there are few studies that have been conducted to analyze this (41). Maillot e.t al. found that in comparing a screen-based setup and a CAVE environment, participants crossing a street accepted fewer gaps and had fewer collisions, while also having better perception of approaching vehicles speeds (42). Small differences in participant behavior have been noted between HMD and CAVE technologies with regard to participant movements (43). Schewbel et. al. found some correlation between a multiscreen setup and the use of a cellphone mounted in a cardboard viewer as a simulated HMD setup (44). Other comparisons have taken into consideration the fidelity of movement, visualization, and sound technology (45–48). Furthermore, there are limited analyses comparing virtual and physical environments to validate the behaviors of participants between the two environments. Early studies analyzed the differences between crossing behavior in IVEs and physical environments with some correlation in behavior while other studies found differences in perception of sound (24)(49)(50). Other studies have discussed the differences between perception of approaching objects between reality and virtual reality (33).

Additionally, there is no standard practice in comparing the effectiveness between simulators using the same technology, either, primarily due to the fact that the technology is relatively new, though, some studies have started conducting post-testing for validation of results. With respect to the more recent studies, identified gaps include a lack of model complexity of the studies conducted, indicating that more work needs to be put into incorporating traffic flow theory and behavior into the IVEs (36)(38)(39). Furthermore, a lack of complexity with respect to what the VRUs can do within an IVE also needs to be addressed, including limitations in walking speed, interaction with vehicles and infrastructure, and modelling streetscapes within the boundaries of indoor laboratory space (37-39). Other gaps in research include studies involving multiple subjects in the same IVE simultaneously in the same or different roles, researching subjects with disabilities in risky scenarios, and utilizing IVEs as a tool for demonstration and education in public forums.

Strikingly, one of the major gaps within research is the lack of validation of pedestrian behavior within simulators with real-world behavior. In the past, the primary approach to validating a simulator has been through the use of post-test questionnaires that offer insight into one's perception of the IVE and how it compared to their real-world experience. Banton observed pedestrians' perception of walking speeds in an early iteration of VR head mounted display and compared those to real-world walking behavior as well as collecting responses to participants' perception of walking speed (23). Schwebel, in 2008, validated a multiscreen simulator by analyzing stated perceptions as well as the safety behavior of participants (24). In 2018, Bhagavathula compared pedestrian behavior in real and virtual environments through the use of questionnaire data, pedestrians never crossed a street but merely observed it and provided feedback on their experiences; however, this study did model the virtual environment off of the real-world environment and participants experienced both scenarios under controlled conditions (39). Also in 2018, Iryo-Asano validated pedestrian perception of distance and subjective danger in VR with that of real-world experience, however, this research focused on pedestrian interactions with other pedestrians or Segway's and did not attempt to validate perceptions based off modelling an IVE off of a real environment or interactions with vehicles (40).

2.4.3 VRU Simulator Categorization

As previously mentioned, IVE simulators have been increasingly used as a means to research VRU behavior and safety. Table 1 has been developed to better illustrate how the trends in technology, immersion, collected data, and analysis of pedestrian VR simulation research have changed over the last two decades.

Table 1 – Categorization of pedestrian studies using virtual reality methodologies.

Report Information			Visual Technology			Level of Immersion					Data Reported					Analysis		
						Agency of Movement												
Year	Author	Laboratory or Affiliated Universities	Single Screen	Multiscreen or CAVE	HMD (O) Oculus Rift (H) HTC Vive (X) Other as listed	*Stationary*	*Dummy*	*Real Time*	Sound	Haptic Feedback	Kinematic	Movement	Eye Tracking (E) Feild of View (F)	Physiological Feedback (E) EEG (P) Passive	Stated Preference	Participants (number and group)	Independent Variables	Statistical Analysis
2002	Simpson et al. (22)	University of Canterbury			X, Virtual Research Systems V8			X				X				24, 5-30 years old	Gap Acceptance, Collision Rate, Cautious Behavior	Descriptive Statistics, Repeated Measures ANOVA
2005	Banton et al. (23)	University of Virginia			X, n-Vision		X				X	X			X	57 undergraduates	Perception of Speed vs Actual Speed, Perception of Speed vs View Angle, Distance Compression	Repeated Measures ANOVA
2008	Schwebel et al. (24)	UAB Youth Safety Lab		X		X			X			X			X	102 children, 7-9 years old 74 adults, 17-52 years old	Gap Acceptance	Descriptive Statistics, One-Way ANOVA
2008	Bart (49)	Tel Aviv University	X			X			X						X	86, 7-12 years old	Collision Rate, Safety of Crossing, Gender	Spearman Correlation, Mann-Whitney U, Wilcoxon
2009	Neider et al. (25)	Illinois Simulation Laboratory		X				X			X	X				36 undergraduates, 18-30 years old	Collision Rate, Crossing Success Rate, Head Movements/Attentive ness	Repeated Measures ANOVA, Bonferroni Correction, Logarithmic Transformation
2010	Schwebel et al. (26)	UAB Youth Safety Lab		X			X		X			X				240, 7-8 years old	Gap Size, Attention to Traffic, Temporal Gap Size	Linear Mixed Models
2011	Bernhard (47)	Technical University of Vienna	X			X			X							48, 19-32 years old	Gender, Average Waiting Time, Auditory Preference	ANOVA, Kendall Rank
2012	Schwebel et al. (30)	UAB Youth Safety Lab		X			X		X			X			X	138 undergraduates, ages 17-45	Gap Acceptance, Collision Rate, Spare Time, Attentiveness	Descriptive Statistics, Binary Regression, Linear Regression, Binary Logistic Regression, Multivariate Regression
2013	Byington et al. (29)	UAB Youth Safety Lab		X			X		X		X	X	F		X	92 undergraduates	Collision Rate, Eye Tacking, Start Up Delay	Descriptive Statistics, Repeated Measures ANOVA
2014	Tzanavari et al. (48)	Immersive and Creative Technologies Lab		X		X			X			X			X	11, 9-10 years old	Attention, Gender, Successful Crossings, Immersion, Noise	Descriptive Statistics
2015	Shen et al. (28)	UAB Youth Safety Lab		X			X		X			X			X	240, 7-8 years old	Collision Rate, Start Up Time, Time To Collision	Descriptive Statistics, Bivariate Correlation, Hierarchical Regression, Bootstrapping Mediation Analysis
2015	Schwebel et al. (27)	UAB Youth Safety Lab		X			X		X			X				44, 7-8 years old	Gap Acceptance, Safe Crossings, Head Movements/Attentive ness	Descriptive Statistics, Covariate, Mixed Effect Logistic Regression, Linear Regression
2015	Tzanavari et al. (33)	Immersive and Creative Technologies Lab		X				X				X				6 male, 8-11 years old	Compliance Rate	Discrete Counts
2015	Sing (51)	University of Warwick		X		X			X						X	14, 26-35 years old	Detection Distance, Recognizability of Vehicles, Vehicle	Repeated Measures ANOVA

																	Detection, Vehicle Impression	
2016	Rahimian et al. (31)	University of Iowa		X		X			X		X	X	F			48 undergraduates	Gap Acceptance, Collision Rate, Attention	Mixed Effects Logistic Regression, One-Way ANOVA, Fischer's Least Square Difference
2016	Montugy (45)	Ifsttar/Inrets		X		X			X						X	80, 20-80 years old	User Preference, Immersion	Chi-Squared, Descriptive Statistics
2017	Schwebel et al. (44)	UAB Youth Safety Lab		X			X					X	F		X	219	Gap Acceptance, Collision Rate, Attention	GEE, Logistic Regression, Poisson Regression with Scaled Deviance
2017	Deb et al. (37)	Mississippi State University			H			X	X		X	X			X	21, 22-50 years old, 5 undergrad, 11 grad or post doc, remaining had grad degree	Gap Acceptance, Collision Rate, Crossing Time	Percentages, Means, Chi-Square, One-Way ANOVA, Repeated Measure ANOVA
2017	Jiang et al. (34)(46)	University of Iowa		X				X	X		X	X				64 undergraduates, 18-33 years old	Gap Acceptance, Collision Rate, Crossing Time, Start Up Time, Interpersonal Distance, Movement Synchrony	Mean, Mixed Effects Logistic Regression
2017	Mallaro (43)	University of Iowa		X	H			X	X			X				32 undergraduates: 16 in CAVE 16 in HMD	Standing Position, Number of Gaps, Gap Size, Timing of Entry, Crossing Time, Spare Time	One-Way ANOVA, Mixed-Effects Logistic Regression, Descriptive Statistics
2017	Maillot (42)	Ifsttar/Inrets		X		X		X	X			X				20, 22-38 years old 40, 62-88 years old	Collision Rate, Accepted Crossings, Inter-simulator Comparison	Descriptive Statistics, Bonferroni
2018	Iryo-Asano et al. (40)	Nagoya University and University of Tokyo			O			X	X		X				X	32	Spatial Perception	Mean, CDF
2018	Farooq et al. (36)	Laboratory of Innovations in Transportation			O			X	X						X	42, >18 years old	Gap Acceptance	Multimodal Logit Model, Percentages
2018	Deb et al. (38)	Mississippi State University			H			X	X		X	X			X	30, 18–47 years old	Crossing Time, Start Up Time	ANOVA, Bonferroni, Regression, T-Test
2018	Bhagavathula et al. (39)	Virginia Tech Transportation Institute and Virginia Smart Road			H		X				X				X	16, 18-35 years old, 11 male, 5 female)	Perception of Safety, Risk of Crossing, Perceived Speed, Perceived Distance	Mixed Model Logistic Regression, Linear Mixed Models, Binomial Regression
2019	Cavallo (52)	Ifsttar/Inrets		X				X	X			X				79, >60 years old	Training Environment, Gender, Accepted Crossings, Collision Rate	Descriptive Statistics, Two-Way ANOVA, Fisher's LSD Test
2020	UVA	ORCL			H			X	X	X	X	X	E & F	X	X			

Definitions for the categorization of Tables 1 can be found in Table 2.

Table 2 – Categorization definitions for Table 1.

Report Information	Year		Year of paper
	Author		Author(s) of paper
	Laboratory or Affiliated Universities		Laboratory or university where the study was conducted
Visual Technology	Single Screen		Subject viewed a single screen as visual source
	Multiscreen or CAVE		Subject viewed multiple screens or was within a CAVE environment
	HMD (O) Oculus Rift (H) HTC Vive (X) Other as listed		Subject viewed environment in head mounted display
Level of Immersion	Agency of Movement	*Stationary*	(Pedestrian) Subject remained motionless or interacted via controller (Bicyclist) subject remained motionless or interacted via controller
		Dummy	(Pedestrian) subject walked on treadmill or stepped off platform but actions weren't translated in VR, movement was only proxy (Bicyclist) subject was on stationary bike but movements were not translated into VR
		Real Time	Subject movements were translated in VR
	Sound		Sound was used in environment
	Haptic Feedback		Interaction with the environment through, vibration, resistance, etc.
Data Reported	Kinematic		Kinematic data includes: speed, steering, direction
	Movement		Movement data includes: special position, body position tracking, head movements
	(E) Eye Tracking (F) Field of View		Eye tracking included in study: field of vision, attention, eye tracking
	Physiological Feedback (E) EEG/ECG (P) Passive		Physiological data collected via EEG of Passive sensor
	Stated Preference		Survey Data was collected in study
Analysis	Participants (number and group)		Number of participants in study and relevant demographics
	Independent Variables		What variables that were studied in the study
	Statistical Analysis		Analysis used to determine impact of variables in study

Chapter 3: Mid-block Crossing Connected Vehicle Application

3.1 Introduction

Research conducted prior to this dissertation as part of my master's thesis involved the development of a mobile connected vehicle application developed to increase safety at mid-block crosswalks. The goal of this research was to design, develop, and test driver behavior and perceptions of a connected vehicle mobile application that warned drivers of a pedestrian's intent to cross at a mid-block crosswalk. This chapter discusses the background, operations, development, testing, and results of this research and how it serves as the motivation for the research in this dissertation, a test case for safety analysis of alternative safety technologies for pedestrians crossing unsignalized crossings, and the inception of the ORCL. The authors of this work were Austin Valentine Angulo and Brian Smith, PhD and professor at the University of Virginia.

3.2 Background

The scope of this project was to develop a mobile application that both pedestrians and motorists can install on their smartphones or tablets to enable users with the ability to communicate with each other at mid-block crossings via discrete safety messages and analyze the safety impacts and performance metrics of said application. Advanced warning messages differ from currently deployed technologies in vehicles, for example automatic braking, as this technology takes a pro-active approach in preventing incidents rather than a reactive approach. Personalized advanced warning messages sent to drivers inform the driver of the pedestrian's intent to cross, potentially increasing the driver's awareness of the pedestrian as well as the pedestrian's intent at the upcoming crosswalk and limiting the number of incidents observed.

This project aimed to expand connected vehicle technology to include vulnerable road users in the connected environment. Mid-block crosswalk treatments vary by region and operational needs; often, a mid-block crosswalk is striped but receives no active infrastructure support, such as flashing warning lights, to warn pedestrians and drivers of a potential conflict. The application was designed to create an advanced warning cyber-physical system (CPS) for a mid-block crosswalk through geofencing – a process of using GPS technology to virtually draw geographic boundaries, or geospaces, which allow mobile technologies to trigger a response when within the defined space – designated areas in which users will be able to interact with each other via smartphone or tablet, as seen in Figure 1.

Figure 1 – The pedestrian (green) and vehicle (red) geofenced areas.

The geofenced cellular network delineates three geofenced areas:

1. A geofence encompassing the mid-block crosswalk and adjacent sidewalk for the Pedestrian Geofence.
2. Two geofences adjacent to either side of the mid-block crosswalk for the Vehicle Geofence.

3.3 Concept of Operations

The advanced warning mobile application was designed such that it used wireless communications to create an environment consisting of stagnant virtual mid-block crossings, overlapping the existing mid-block crossings, which users could interact with. When a pedestrian is in range of the designated crossing, the virtual environment recognizes that a user is present and enables the user to broadcast their presence and intent to cross at the crossing. Drivers need to be equipped with the application so that they may interact with the virtual network, as well. When the driver is within a designated range of the virtual crosswalk and a pedestrian broadcasts a notification of their presence at the mid-block crossing using the mobile application, a visual and audible advanced warning message is transmitted to the driver, warning them that a pedestrian is present.

The application was designed to run as the primary screen on the phone and will serve as a proof of concept. Further development can have the application operate in the background of the smart device or integrated into other GPS technologies, seamlessly allowing users to view their GPS and be alerted from the crossing via visual and audible messaging.

This application needs only standard signage, pavement markings, and cellular signal from two smart devices (one in vehicle and one on the pedestrian's person) in order for proper operation at a mid-block crossing. The application was designed so that it would limit the cost and materials needed to operate and maintain active warning technology at mid-block crossings.

3.4 System Overview

The CPS was created using localized, designated geospaces, using GPS navigational systems (in this instance, Google Maps) at mid-block crossings. Users in the geospaces have the ability to interact with the virtual crosswalk; the interaction between users and the environment is limited to user request and solely personal-message oriented. Users have the option to define themselves as a Pedestrian or Motorist upon opening the application and are allowed to alter roles between trips. The system architecture and data flow for messaging of the CPS and the user interface of the application is shown in Figure 2.

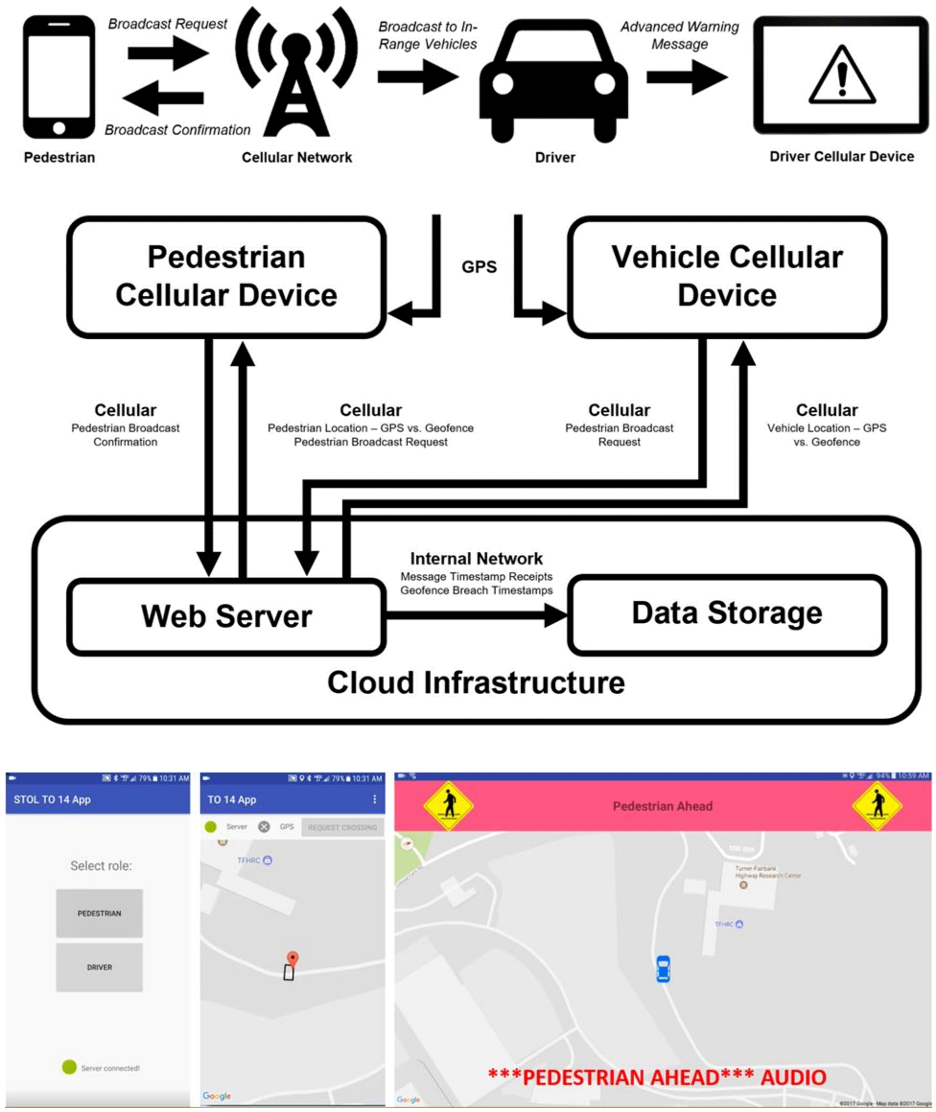


Figure 2 – Data flow, system architecture, and user interface of phone app.

3.5 Data Collection for Analysis

In this report, four major data types were considered to understand the behaviors of drivers with the advanced warning message. The first data source considered was drivers' reaction to the warning message. This was defined as the percentage of drivers stopping for the pedestrian with and without the advanced warning message. The second data source considered was drivers' stated preference data. This was collected through a posttest questionnaire regarding the drivers' perceptions of the application. Responses were recorded on a five-point Likert scale ranging from 1 to 5 – with responses of 1 indicating strongly disagreeing with the statement and responses of 5 indicating a strong agreement with the statement – and analyzed perceptions of how much drivers believed it improved their awareness of the pedestrian, whether drivers found the technology distracting, and whether or not drivers would like to see this technology integrated into commonly used GPS routing applications. The third data source considered was drivers' collected eye tracking data. The eye tracking software, SmartEye, collected the location the driver is looking as a vector in 3-dimensional space. This information was overlaid on the recorded video from the forward-facing camera installed in the vehicle to analyze where the driver was looking during the experiment. The last data source considered was the drivers' kinetic data which was collected via the on-board vehicle control area network (CAN) bus. The vehicle's standard data collection protocol was deemed appropriate as it collected speed (MPH), location (GPS), acceleration rate, deceleration rate, steering wheel angle, and break application (a binary measurement is the brake is pressed or not pressed).

3.6 Results

During the daytime, a total of 92 subjects were tested and during the nighttime a total of 32 subjects were tested for a grand total of 124 test subjects. The 124 subjects were recruited from the northern Virginia area, representative of the community that lives in the northern Virginia area.

3.6.1 Yielding Rates & Odds Ratios

The first measure of effectiveness that was considered was the effect of the warning application on the driver's yielding rate. During the daytime, 45% of drivers in Group A stopped for the pedestrian without the warning during Lap 1, whereas on Lap 2 with the warning they stopped 80% of the time. Group B during the day stopped 73.1% of the time with the warning during Lap 1 and 63.5% of the time without the message during Lap 2. During the nighttime, drivers stopped for the pedestrian75% of the time without the warning during Lap 1 and 90.6% of the time with the message during Lap 2.

The odds ratios analysis showed that drivers were more willing to stop for the pedestrian with a warning message than without one. In particular, drivers on their first exposure to the pedestrian were 2.44 times more likely to stop for the pedestrian during the day and 1.79 times more likely to stop for the pedestrian at night with the advanced warning. These results are consistent with previous studies and regarding the effects of RFB activation and driver yielding rates along similar roadways (53-55).

Furthermore, the odds ratios were conducted for questionnaire responses indicating the likelihood that the driver would be in agreement with the statements provided in the questionnaire regarding whether the warning increased the drivers' awareness of the pedestrian (Increased Awareness), whether the application is a technology drivers would like to see incorporated into other GPS applications (Technological Acceptance), and whether drivers didn't find the application distracting (Found Not Distracting). For each survey question, it was found that the driver was more likely to give positive feedback for the application if the driver stopped for the pedestrian. With a confidence value of 95%, only the Increased Awareness category saw a lower confidence value lower than 1, indicating that it is possible that the application increased all drivers' awareness of the pedestrian, regardless of whether the driver stopped or didn't stop.

3.6.2 Binary Logit Model

To best understand the impacts of the many variables in the experiment on the yielding decisions by the drivers, binary logistic regression analyses were conducted on select cases for the study. The binary logit model for this study, using a confidence value of 95%, follows the following form:

$$Y = log_b \frac{p}{1-p} = \beta_0 + \beta_1 X_1 + \cdots + \beta_n X_n$$

Where:

Y = Expected Outcome (i.e. Stop or Didn't Stop)

p = probability of stopping for pedestrian

β = "degree of change" coefficient

X = independent variable (i.e. Age, Warning Message, Gender, etc.)

n = subject number

Multiple iterations of this model were conducted to best understand the impacts of each variable analyzed. The key factors analyzed were:

- Whether or not the driver received the warning message
- What lap the driver received the message on
- The time of day
- The age of each participant
- The sex of each participant
- The speed at which the driver was travelling when the message was received

- The percent time the driver spent looking at the pedestrian

The first binary logit model found that younger drivers were more willing to stop for the pedestrian, that drivers were more likely to stop for the pedestrian during the nighttime than the daytime, and that drivers were more willing to stop for the pedestrian with the warning message. Both the message and time of day variables had larger coefficient values within the model results, indicating that these had a strong influence over whether or not the driver stopped for the pedestrian.

The second binary logit model included the eye tracking data from the study. The significant variables in this model form were found to be age, time of day, and reception of the message. Considering this subject group, it was found that younger drivers were more willing to stop for the pedestrian, that drivers were more likely to stop for the pedestrian during the nighttime than the daytime, and that drivers were more willing to stop for the pedestrian with the warning message. All of these variables had larger coefficient values, indicating that they had a strong influence over whether or not the driver stopped for the pedestrian. Eye tracking data was shown to not be a significant factor.

The third binary logit model included data which were part of the daytime experiment since only the daytime experiment alternated the lap order in which drivers received the warning message. The significant variables in this model form were found to be age, lap order, reception of the message, and the percent time spent looking at the pedestrian. Considering this subject group, it was found that younger drivers were more willing to stop for the pedestrian, that drivers were more willing to stop for the pedestrian on their second lap, that drivers were more willing to stop for the pedestrian the longer they looked at them, and that drivers were more willing to stop for the pedestrian with the warning message. The reception of the message, age, and percent time looking at the pedestrian variables had larger coefficient values, indicating that these had a strong influence over whether or not the driver stopped for the pedestrian.

3.7 Conclusions

This research aimed to develop a cyber physical, C-V2X application that could be easily integrated into typical GPS navigation applications that provided proactive, advanced warning messages to drivers of pedestrians' presence and intent to cross at mid-block crosswalks. From the analysis conducted, a few conclusions can be made that indicate the positive performance of the advanced warning message.

1. First, the odds ratio tests for the warning vs no warning case on lap order shows that, across the board, those who received the advanced warning message were more willing to stop for the pedestrian than without it.
2. Second, it was found that in the odds ratio comparison between driver reaction (stopped vs didn't stop) and stated responses in the questionnaire that those who did stop for the pedestrian were more likely to rate the application positively. An argument can be made, however, that the ideal scenario for this odds ratio test be 1 for each questionnaire statement, indicating that there isn't a difference in perception of the application between those that did and didn't stop for the pedestrian, with all subjects reporting positive feedback. This in mind, the most important questionnaire response, whether the application increased the drivers' awareness of the pedestrian, has an odds ratio of 1.35 and a confidence interval below 1. In this analysis,

88.9% of the subjects indicated that the application increased their awareness of the pedestrian, validating this ideal scenario.

3. Third, regarding the binary logit models, it can be concluded that driver age, the time of the day that subjects were tested, and the presence of the advanced warning message all had strong, significant impacts on the rate at which drivers stopped for the pedestrian. Most importantly, the presence of the advanced warning message was found to be very significant across all models, showing an increase in the likelihood for the driver to stop for the pedestrian, further indicating that the message had a positive impact on driver behavior.

3.8 Discussion and Motivation

Upon completion of this research and due to the overwhelming positive reception and compliance with the application from drivers, it became apparent that the application should be tested with respect to the people who would be using it – the pedestrians. If it is not well received by the pedestrian, it would most likely not be used and therefore would be moot. Furthermore, while the application might show positive impacts in safety from the driver’s perspective, pedestrians may behave rather differently with it – e.g., would they trust that drivers would stop and walk out in front of them?

Testing this application in a real-world environment would require a lot of control to account for pedestrian safety – in the driver testing, the pedestrian could be controlled and wouldn’t cross unless it was safe, however, when testing pedestrians, it is much harder to know if, how, or when to stop for them. Since real-world pedestrian testing seemed unrealistic and unsafe, VR simulation was deemed the only viable way to conduct any testing with pedestrians and this application.

Not only would virtual reality negate the safety issues inherent in real-world testing, it would provide a platform in which we could test the application alongside other technologies, such as rapid flashing beacons, to determine how the application compares in performance and technological acceptance. Additionally, virtual reality technology has come a long way and now offers a multitude of capabilities that were not possible in previous virtual reality experiments that would make pedestrian testing very realistic – e.g., tactile feedback, stereo sound, high resolution imaging, high frame rates, eye tracking, and free range of motion.

The benefits of the mobile phone crossing application coupled with the advancements in commercially available VR technology strongly motivated me to pursue research into the development of a pedestrian VR simulator within which I could test out multiple scenarios and environments and obtain results that would be directly applicable to real-world designs and operations.

Chapter 4: Methodology - Developing a Virtual Reality Pedestrian Simulator

4.1 Introduction

The development of the ORCL considered the many previous technologies, strategies, and results of previous simulators as discussed in Chapter 2. The goal of the ORCL was to build a state-of-the-art VR simulator utilizing commercially available technology so that the research conducted in lab and as presented in this dissertation could be readily replicated and adapted to suit the application needs of other real-world environments or research. Furthermore, the development of the ORCL set out to expand the capabilities and types of data collected within pedestrian simulation research to gather comprehensive, multi-modal data to further the understanding of pedestrian behavior and preferences in ways previously not done.

4.2 Elements of Pedestrian Simulator

All stages, excluding the real-world observation portion, of this experiment were conducted in the ORCL in D107 of Thornton Hall at the University of Virginia. The lab is equipped with state-of-the-art virtual reality equipment, computers, and bicycle trainer for testing both pedestrians and bicyclists. The lab has a designated 2x11 meter space for participants to walk around in while being tracked in the virtual environment.

4.2.1 System Architecture

In order to collect the multimodal data desired, multiple components needed to work together in synchronicity to understand VRU behavior within IVEs. The ORCL's simulator system architecture is shown in Figure 3 below, detailing all of the technology, software, communications network, and associated data flow.

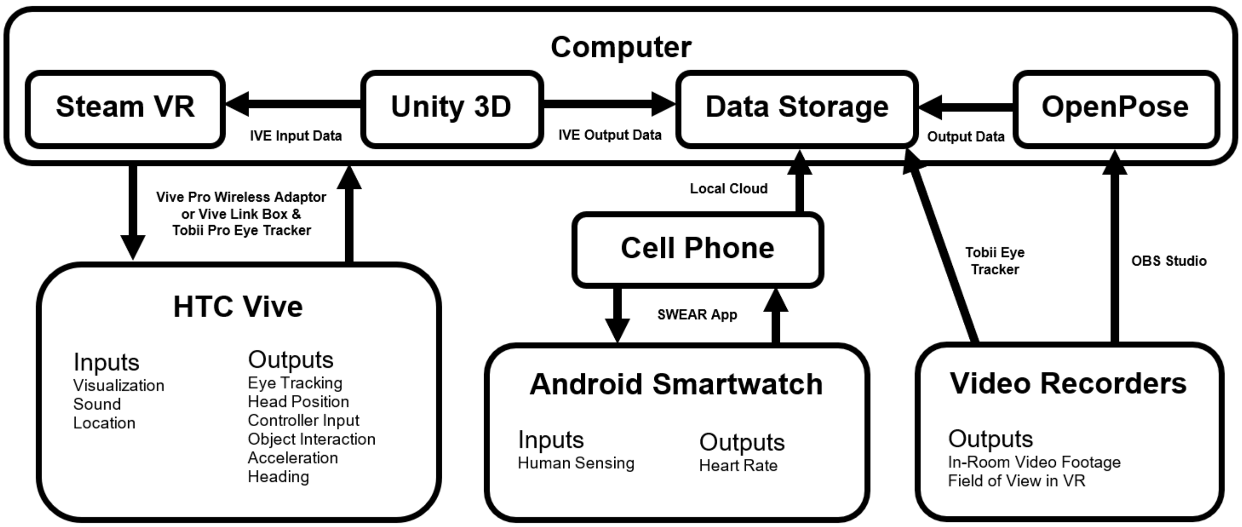


Figure 3 – System architecture for pedestrian virtual reality simulator.

4.2.2 Equipment

This section provides information about the equipment selected for this experiment as well as reasoning behind the equipment choices for the ORCL as it relates to past research.

HTC Vive Headsets

Two, identical, HTC Vive Pro headsets with their accompanying controllers will be used during experimentation. The HTC Vive Pro has a resolution of 2880 x 1600 (615PPI) pixels with a refresh rate of 90 hz and is run on SteamVR. The maximum range of the headsets, wired, is 100m squared. The headsets have built in headphones with in-line amplifiers and a field of view of 110 degrees. Movement is traced with an accelerometer, gyroscope, lighthouse 2.0 laser tracking system, and dual front-facing cameras. The headsets have been equipped with the HTC Vive Pro Wireless

Adapters, which supports a 6 x 6 m space for accurate tracking and operates on a zero-latency wireless communication.

The HTC Vive Pro Eye is capable of running high resolutions and frame rates, provides a wide field of view, has movement tracing capabilities, and is compatible with SteamVR. HTC Vive Pro Eye headsets were chosen as they provide top of the line performance in all aspects of VR performance (frame rate, level of detail, comfort, and ability to plug and play ability with SteamVR). The included controllers allow the user to interact with objects in the virtual environment, as an extension of their hand.

There are two major competitors on the market offering high end, commercially available virtual reality headsets – the Oculus Rift and the HTC Vive. At the time of purchase, HTC offered a wide range of headset options, specifically the Vive Pro Eye with integrated Tobii eye tracking software that would work seamlessly within SteamVR and the Oculus didn't. Furthermore, the Pro version of the HTC headsets had a higher resolution than the Rift, offering a more immersive experience. Additionally, at the time of purchase, only HTC offered a wireless adapter so that users could move around freely within a large space without being tethered to the computer by a cable or having to carry around a laptop with a backpack in it. Because of these options, it was clear that the HTC Vive Pro Eye offered the most immersive experience while also allowing us to collect data that had yet to be collected previously.

Computer Hardware and Software

All IVEs used in this experiment were developed in Unity and run through the SteamVR platform. The ability to render highly detailed VR environments at high frame rates (>30 FPS) is limited to the capability of the computer hardware the simulations are being run on. For use in the ORCL, high end computing equipment was chosen so that computational performance would not be a limiting factor in development and testing. High performance factory overclocked Nvidia 1080Ti graphics cards run through Scalable Link Interface, an Intel Core i9-7920X, 64 GB of DDR4 RAM at clock speeds of 3600MHz, and M.2 Solid State Hard Drives were installed in the lab computer.

The hardware within the computer cannot necessarily be compared to that used in other studies as it is not seldom referenced or listed; however, the computer was tasked to simultaneously collect three videos at 1080p while also running the pedestrian simulation, thus it was paramount to build the computer with the most high-end equipment on the market to assure that environment rendering and stability, data collection speeds, and information exchanges would not bottleneck at any component within the system during testing. Unity and SteamVR were chosen as they are simply the 'go-to' when building VR games and simulations. The Unity platform is widely used and offers an online asset store with free or purchasable assets one could import into their VR environment without having to make from scratch (e.g. cars and trees) to expedite the process of environment construction. SteamVR was chosen as the client to run the HTC headset because it was not only used in the development of the HTC equipment, but it is also the default client when using Unity. This approach is standard in all of the previous VR experiments utilizing either Oculus or HTC HMDs.

Physiological Responses

Our platform uses an android smartwatch that is equipped with the "SWEAR" app for collecting long-term data from smartwatches (56). The SWEAR app records heart rate, hand acceleration, audio amplitude (noise level), and gyroscope. All these data from smartwatch will be stored on the local device and then can be uploaded to the cloud.

There are multiple physiological sensing devices on the market that offer professional grade physiological data tracking and accuracy; however, these devices are expensive and often rather difficult to sync up together with the data. Furthermore, the Fossil smartwatches used in this experiment were readily available within the department and connected to the department server so that time synchronicity wasn't of concern since the smartwatches were the only experimental sensors not connected to the main computer running the simulation. Two other devices were considered for this experiment, the Empatica E4 smartwatch and Shimmer3 ECG (electrocardiogram). The Shimmer ECG required sensor placement on the tips of the fingers on subjects, interfering with their ability to interact with the controllers and thus was ruled out. The Empatica smartwatch, when compared to the Fossil smartwatch data, was more variable and less accurate and thus was rejected for use.

Eye Tracking

The eye tracking features of HTC Vive Pro Eye in Unity comes from integrated Tobii Pro eye tracker. It can be utilized to track and analyze eye movement, gaze data, and focus for further data analysis. By designing interactions with other objects, it can help to create more immersive virtual simulations, gain insights about user performance, and improve understanding of pedestrian behavior.

As previously mentioned, eye tracking is a technology that has been used in the past, but only for capturing the field of view of the test subject in pedestrian simulation. With the HTC Vive Pro Eye, Tobii eye tracking allows us the ability to know exactly where a subject is looking. This data is novel in offering an understanding for what influences pedestrian behavior and attracts their attention.

Video Recording

There will be two external video recording devices in the lab that will be capturing each subject's movements during experimentation on 1080p. These recordings will be used to understand subject movements and reactions. The body position data can be extracted from these videos by OpenPose. Used in conjunction with the movement tracking of the VR headset and controllers, this video footage can help determine how subjects were reacting during experimentation for better behavioral analysis.

Body tracking is a novel approach in understanding pedestrian behavior in VR simulation. As discussed in Chapter 4.2.3, body tracking not only allows for movement tracking, but limb tracking, providing insight into how a subject physically reacts to the environment and offers new insight into how a person actually behaves compared to stated behavior in surveys.

Figure 4 below is a screenshot of the real time data visualization during a pilot study with one of the experimenters in VR. Within this Figure is the lab space, body tracking, field of view from subject point of view, pupil diameter, eye position, relative position in VR, relative heading in VR, controller position, heart rate, and hand acceleration.

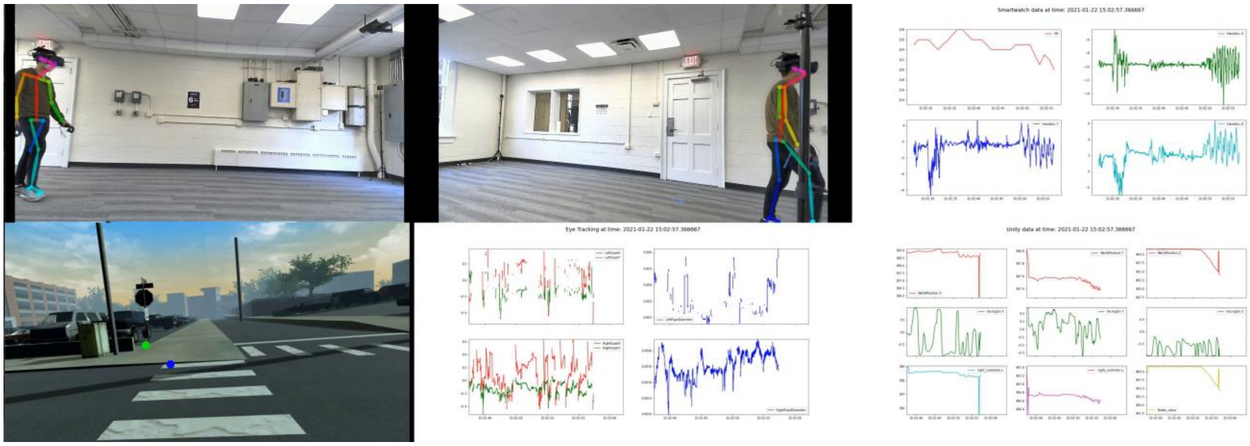


Figure 4 – Real-time data visualization screenshot of physiological and position data for pedestrian VR experimentation.

4.2.3 Data Framework

As discussed in 2.4, the equipment selected will help us address the gaps in knowledge previously unstudied in other labs and IVEs. Table 3, below, provides the developed framework by which we collected data and what type of data is collected.

Table 3 – Data framework for pedestrian VR experimentation.

Data Source	Method	Data Type
Surveys	Pre-Survey	Likert
	Post-Survey	Likert
Virtual Sensors	HTC Vive	Movement/Position
		Vive Controller Input
Physiological Sensors	Android Smartwatch	Heart Rate
	HTC Vive	Eye Tracking
	Cameras & OpenPose	Body Position

This framework is focused on three primary sources of data: survey, virtual sensor, and physiological data.

Survey Data

Survey data was a common source of data as shown in Chapter 2, with most studies collecting stated preference data of some kind within their studies; however, as shown in Chapter 2.4.5, few studies report this data as an independent variable in their analyses as a means of understanding VRU preferences, immersion and behavior. At the ORCL, we have developed pre- and post-experiment surveys to collect demographic, emotional state, VR familiarity, travel behavior, travel mode preference, technological preference, and self-reported immersion data to develop a comprehensive story for understanding why VRUs make the choices they do within the IVE. These data help to identify factors that may drive decision making. For example, someone who walks daily to work may have faster walking speeds, which may correlate with why they may have walked faster within the VR environment.

Virtual Sensor Data

Virtual sensor data covers a broad range of data types. As shown in Table 1, virtual sensors are used to collect movement and kinematics, however, virtual sensors can be leveraged to collect better data as well as make IVEs more immersive and interactive. At the ORCL, we have taken advantage of new VR technology to collect movement data as well as position data within the IVE so that a subject's relative position to other objects within the environment can be known. Furthermore, we've utilized the Vive Controllers so that users could interact with objects within the virtual environment, something never before done as shown in the Haptic Feedback column of Table 1. Haptic feedback within the experiments of this study includes the use of virtual touch – e.g., pushing a button on a flashing beacon and selecting a button on a virtual phone. Both of these instances are interactions with objects that only exist in the virtual environment, yet behave and respond as if they were real.

Physiological Sensor Data

Physiological sensor data refers to data collected that can help understand subject behavior within the IVE. At the ORCL, we have adopted a few methods for collecting physiological responses such as heart rate, eye tracking, and body position. As shown in Table 1, multiple studies collected spatial position and kinematic data for analysis, however, none collected detailed body position data. The distinction between spatial position data and body position data is that spatial position data is collected via video recorders for understanding where somebody is within a space, whereas body position data uses video recorders for understanding how the limbs of the body move within the space during the experiment. This data is used for interpreting many possible instances within experimentation that new insight into pedestrian testing – e.g., someone pulling their arms and hands in towards their chest may indicate a fear response by shielding their vital organs instinctively. This data can be cross-analyzed with survey data to compare subject observed behavior against stated preference to fully capture the differences between what people do and what they say.

4.3 Modeling a Real-World Environment in Virtual Reality

4.3.1 Corridor Selection and Simulated Environment

The selected corridor for this study is a section of Water St W and Water St E between 2nd St SW and 2nd St SE in Charlottesville, Virginia. An aerial map of the designated corridor is displayed in Figure 5.

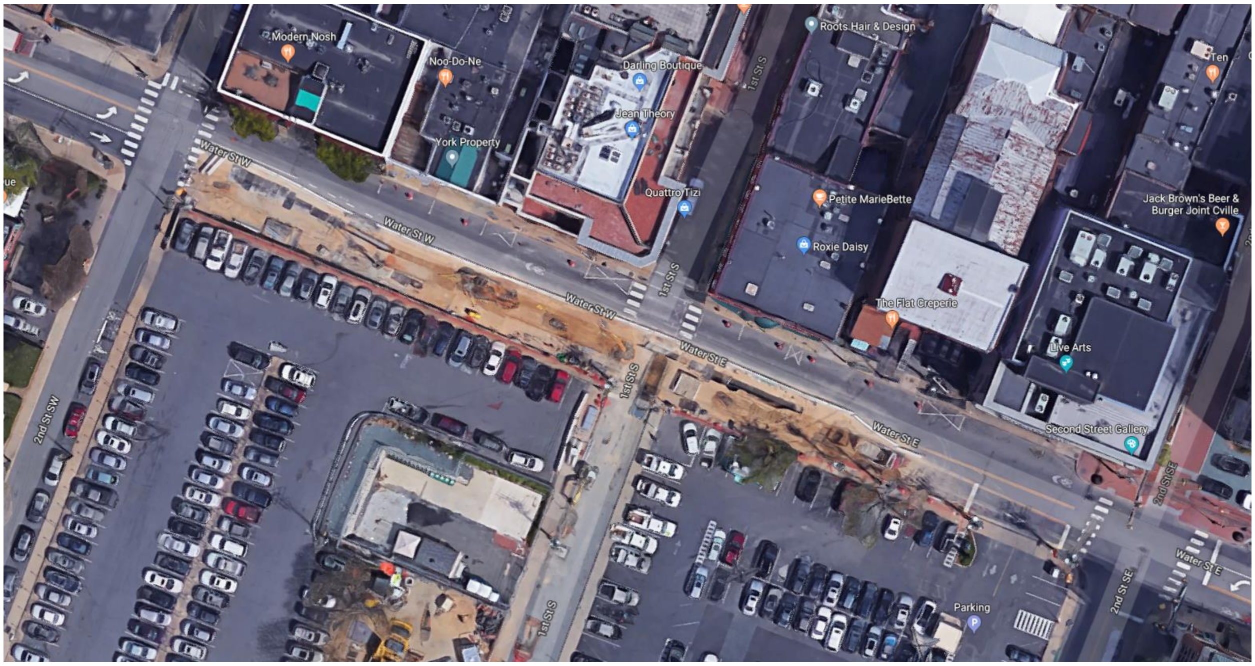


Figure 5 – Aerial image of Water Street corridor (57)

This corridor was selected as the site for study due to the heavy pedestrian traffic it experiences due to downtown mall foot traffic and commuting and for being identified as a hot spot for pedestrian-vehicle accidents in VDOT's Pedestrian Safety Action Plan Map Viewer (58).

Figure 6 below depicts a snapshot of Water Street from Google Maps as well as a screenshot of the in-development virtual environment of Water Street designed in Unity. The two crosswalks at 1st St S (the intersection shown) are the designated midblock crossings for this experiment. 1st St S in the northbound direction towards Water St is a one-way road that has low traffic volumes and in the southbound direction is a small access road to the mall that does not extend through the downtown pedestrian mall, thus, has no through traffic. Due to these conditions, the intersection operates similarly to a standard midblock crossing and is deemed appropriate for testing for this research. Furthermore, data collected through video recording of the site can be limited to instances where no vehicles are present and attempting to turn onto Water St from 1st St

S and no vehicles will be present in the virtual environment to ensure consistency between the real world and virtual conditions.

Figure 6 – Ground level perspective comparison of virtual reality and real-world environments (59)

4.3.2 Observation Setup

A video camera will be installed on existing infrastructure away from public interference and will continuously record driver, pedestrian, and cyclist behavior at the location. This data will be used as a reference for understanding real world use of roadway facilities and compliance with the infrastructure and road rules.

Real world observations were conducted by installing four MioVision Scout cameras (named A, B, C, and D) at the intersections of 2nd St SW, 1st St S, and 2nd St SE along Water St. The placement and angles of these cameras are shown in Figure 7 below.

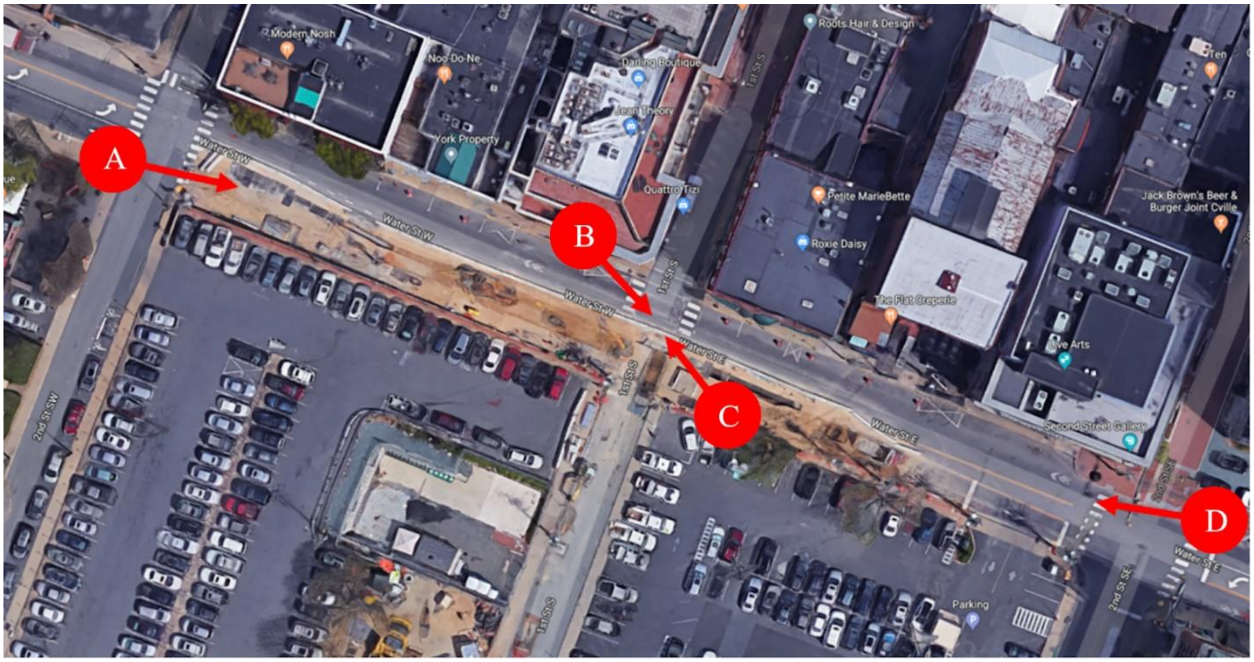


Figure 7 – Camera positioning for observational data collection on Water Street Corridor (57)

The field of view of each of the four cameras is shown below in Figure 8.

Figure 8 – Field of view screenshot from observational cameras

Cameras A and D were placed at either end of the observation corridor in both the east and westbound directions, respectively, to capture approaching vehicle data as well as mid-block crossing outside of the crosswalk as well as any other information in the general vicinity that may have been pertinent to any individual crossing. Cameras B and C were placed in the eastbound and westbound directions, respectively, with the entirety of the same crosswalk of the intersection of Water St and 1st Street South in view to collect crossing behaviors, approaching vehicle data, and any other information in the direct vicinity of the crosswalk that may have been pertinent to any individual crossing.

The cameras were installed during 2 weeks of August 2019 and collected two periods of data: Tuesday 12 am to Thursday 11:59 pm. The recordings too place on August 20-22 and 27-29, midweek. This time period was selected as it falls in the middle of summer when most people are walking around the mall and after students have returned to UVA Grounds (even though Water St is not on Grounds, it was deemed appropriate to record footage of Charlottesville when students have returned to Grounds as Charlottesville is most heavily populated at this time, thus, increasing the likelihood of getting a greater number of pedestrian crossings for data analysis.

4.3.3 Real World Analysis

Data Cleaning

Data from the videos was recorded by two undergraduate students within the project team under the guidance of graduate researchers. The peak hours of 7am to 9am and 4pm to 6pm were deemed appropriate for analysis of the pedestrian data as they were the hours in which the most pedestrians and vehicles were observed on the road, yielding enough data for analysis and comparison with the virtual data to be collected. The two undergraduate recorders were given excel documents created by the graduate researchers with data fields and instructions for recording the events as seen in the environments. Multiple iterations of random hours of the datasets were conducted to improve the recording document fields, designs, and definitions as well as improve the understanding and accuracy of the undergraduates until the graduate researchers and professors on the team felt that further improvements would yield diminishing returns.

Once the two datasets from each researcher were collected, the dataset was reduced by keeping only the data which both data collectors had recorded identical values for every performance metric. Of the dataset of 957 recorded crossings, the two data researchers had both recorded 791 – meaning 166 crossings only one researcher had recorded, thus, they couldn't be used. Of the 791 crossings that both researchers had recorded, 420 of them were identical. This dataset of 420 identical recordings represents 43.9% of the 957 crossings recorded. Furthermore, since preliminary testing within the virtual environment was to be done by analyzing gaps with vehicles approaching from only one direction, the real-world dataset had to be reduced further to only represent instances where traffic was approaching from one direction. Of the dataset of 420 identical recordings, 196 crossings had traffic approaching from only one direction before a gap was selected and the pedestrian finished crossing the street.

Of the 196 crossings recorded at Water Street and 1st Street South, 251 gaps were observed. These gaps were observed a third time by a graduate researcher to finalize the validity of the crossings and selected gaps. 49 of the 251 observed gaps were removed from the dataset because of instances that may have impacted the gap acceptance of pedestrians (e.g. vehicles entering roadway from being parked on the side of the road or loading vehicles stopping on top of the crosswalk and blocking sight distance). 202 of the 251 gaps were deemed as appropriate for testing after this process.

Performance Metrics

Multiple performance metrics were collected in watching the video footage and are described in Table 4 below.

Table 4 – Performance metrics collected during observational data analysis, interpretation of data, and how data was collected

METRIC	UNITS	INTERPRETATION	HOW IT IS MEASURED
GAP SIZE	Seconds	Gap size is the headway time between approaching vehicles and aides in the understanding of perception of safety and level of risk pedestrians are willing to take when crossing the road.	Gap size was measured by finding the headway time between vehicles at a specific location in the environment.
START UP DELAY	Seconds	Start up delay will aid in the understanding of pedestrian comfort. Time spent waiting at the crosswalk before crossing can be indicative of the pedestrian’s trust that drivers will yield for the pedestrian.	Timestamps are collected for when the pedestrian reaches the edge of the crosswalk and when the pedestrian steps off of the curb onto to the roadway. No start up delay is measured when a pedestrian doesn’t visibly stop at the crosswalk.

START UP DELAY IN CROSSWALK	Seconds	Start up delay in the crosswalk is indicative of pedestrian behavior while crossing. Pedestrians may stop mid-crossing to determine approaching vehicle behaviors, capturing this data may be indicative of pedestrian trust in driver behavior.	Timestamps are collected for when pedestrians stop during their crossing on the roadway and resume crossing. Pedestrian must come to a full stop for it to be considered a start up delay mid crosswalk.
CROSSING TIME	Seconds	Crossing Time is the total time pedestrians spend in the crosswalk while crossing. This metric is used in determining pedestrian average crossing speed.	Timestamps are collected from the moment a pedestrian steps foot onto the roadway to cross the road and the moment a pedestrian steps foot onto the curb after crossing. Total crossing time does include the start up delay time within the crosswalk, but not the start up delay.
PEDESTRIAN USE OF CROSSWALK	Yes/No	This metric refers to whether the pedestrian was within the crosswalk during their crossing, or whether the pedestrian chose to cross outside of the crosswalk. Pedestrian use of the crosswalk can be indicative of typical pedestrian behaviors at crosswalks as well as their comfort (i.e. pedestrians may be more willing to cross at a crosswalk when vehicles are present vs pedestrians may cross the street midblock if no vehicles are approaching)	For both the start and the end of pedestrians' crossings, pedestrians' use of the crosswalk is indicated by a Boolean Yes or No data field. If the pedestrian is directly within the crosswalk, the response would be Yes. If they crossed outside of the crosswalk, or if they deviated from the crosswalk mid crossing, the response would be No.
PEDESTRIAN START POSITION	Directional	At the Water St intersection, there are four corners from which a pedestrian could cross the crosswalk, two on the northside and two on the southside. This metric is used to determine where pedestrians cross from to help calculate crossing time and determine the most often used crosswalk at the location.	Each corner of the intersection was given a corresponding number to indicate whether the crossed at the North or South sides of the street and the East or West crosswalk.
AVERAGE CROSSING SPEED	Mph	Walking speeds will aid in the understanding and identification of a dart/dash movement, whether the pedestrian may have chosen a gap they are uncomfortable with, or whether the pedestrian feels anxious when crossing.	Average crossing speed is calculated by taking the total time spent crossing and dividing it by the distance across the roadway. Start up delay in crosswalk is subtracted from the total time spent crossing in order to prevent inaccurate crossing speeds. *
NUMBER OF VEHICLES PASSED BEFORE CROSSING	Count # / Directional	Counting the number of vehicles passed before the pedestrian begins crossing will be indicative of the gap sizes that pedestrians are rejecting.	Count number of vehicles passing. Afterwards, determine rejected gap sizes by timing headways with stopwatch and record.
PEDESTRIAN REACTION TO LAST VEHICLE	Directional / Yield Behavior	The pedestrian reaction to the last vehicle metric will indicate whether pedestrians waited for all vehicles to pass before crossing, whether vehicles yielded for the pedestrian, or whether the pedestrian chose a gap they felt acceptable for crossing. This behavior is indicative of pedestrian safety as well as comfort. Different interpretations can be drawn from this data as this is considered the pedestrians accepted gap. The gap size accepted can indicate that: • The pedestrian felt it was a considerable gap size to cross during • The pedestrian's acceptable gap size reduced over wait time • The pedestrian trusted approaching vehicles to stop for them when they began crossing • The pedestrian was waiting for a vehicle to yield the right of way	Record whether there was a vehicle approaching when the pedestrian began the crossing from both directions. Record whether the pedestrian waited for the vehicle to stop. If the pedestrian didn't wait, then this is the pedestrian's accepted gap.

In validating the VR simulator for pedestrians, two of these performance metrics were marked as the key identifiers of crossing behavior and safety: gap size and crossing speed. Gap size helps identify what gaps pedestrians feel safe to cross during and comparing the real-world and VR gap acceptance distributions will help in validating whether pedestrians' perception of safety is similar to that at the real-world crossing. Crossing speed is also important, as it is indicative of the safety of a pedestrians crossing. As previously discussed, dart/dash movements across crosswalks are unsafe crossing behavior and lead to many accidents. Comparing crossing speeds will not only help in validating pedestrian behavior inside the VR environment, but also aid in determining whether safety treatments impact crossing behavior.

4.3.4 Gap Selection

202 gaps were observed by pedestrians at the Water Street and 1st Street South mid-block crosswalk. 85 of these gaps were rejected and 117 of them were accepted. To determine the critical gap of this mid-block crosswalk when vehicles are approaching from only one direction, the rejected and accepted gap distributions were plotted as shown in Figure 9.

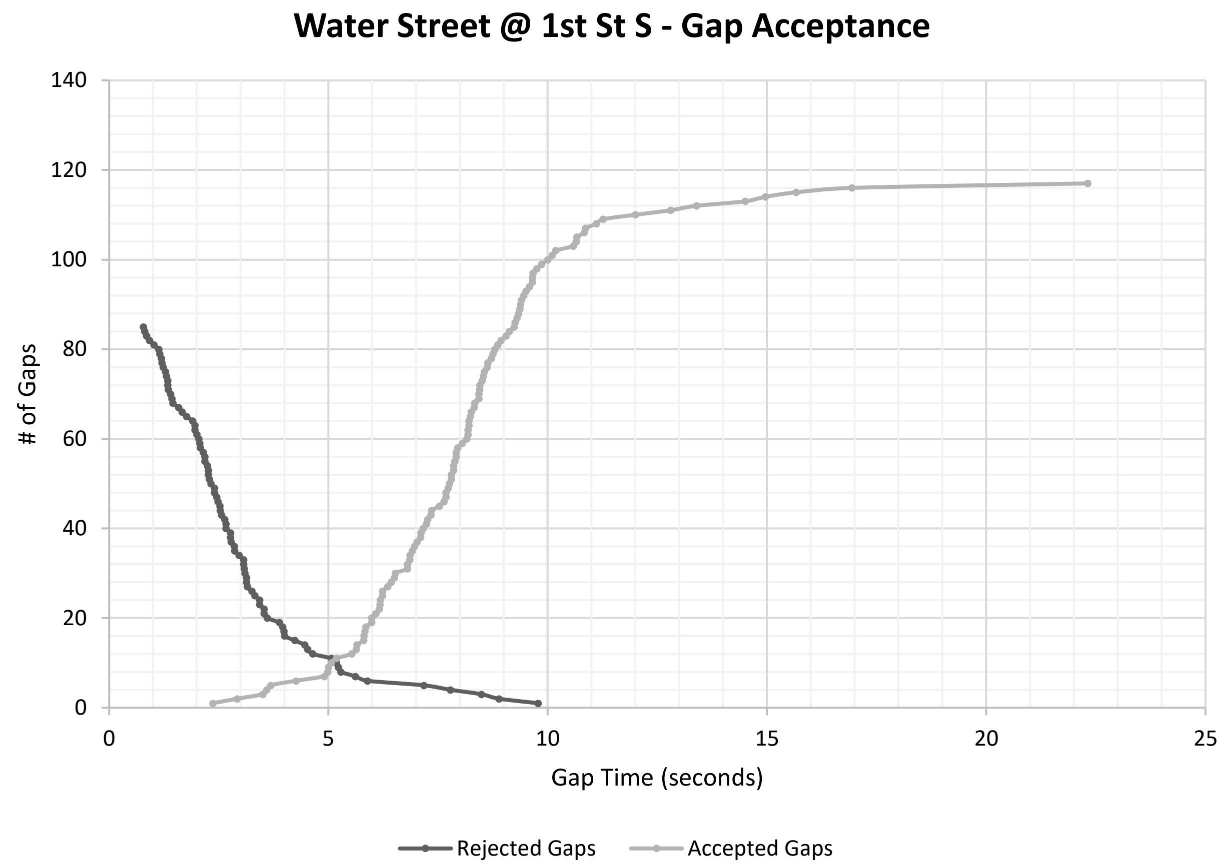


Figure 9 – Gap acceptance at Water Street and 1st Street S unsignalized crossing

Figure 9 shows that the accepted and rejected gap distributions overlap at 5.12 seconds, indicating that 5.12 seconds is the critical gap time in which pedestrians decide to accept a gap, rather than reject it. Table 5 below provides some descriptive statistics of the two distributions.

Table 5 – Descriptive statistics of gap acceptance at Water Street and 1st Street S

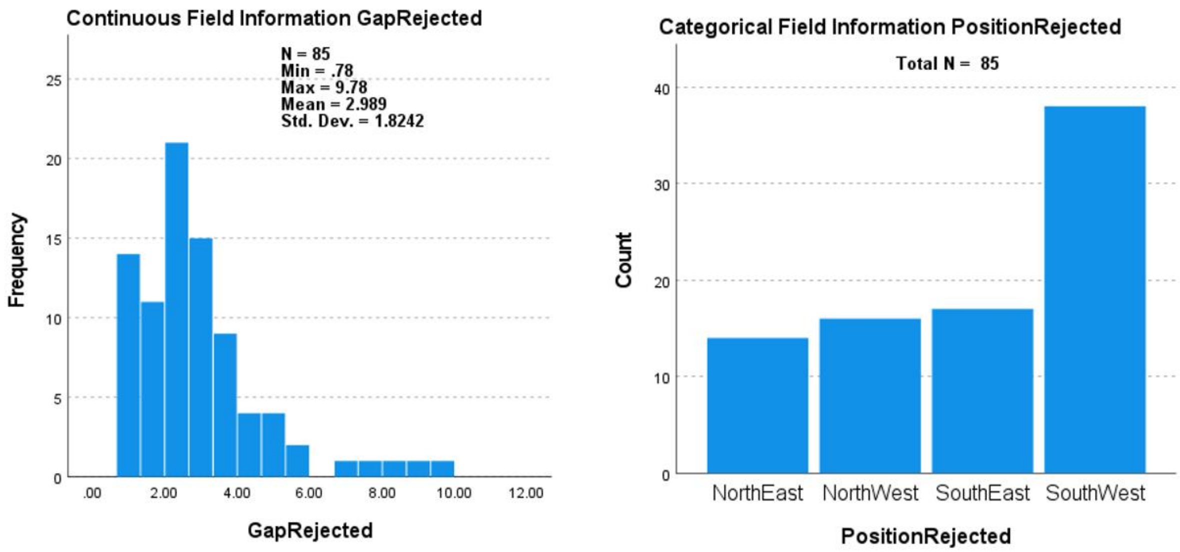
Accepted		**Rejected**	
Median	8.05s	Median	2.56s
Count	117s	Count	85s
Critical Gap		**5.12 seconds**	

Crossing Location Gap Comparison

Within the real-world observation, pedestrians crossed Water Street from four different corners of the intersection. To make sure that the sample of 202 gaps was valid for use in generating an empirical distribution from which to generate gaps within the virtual environment, statistical analysis of both the rejected and accepted gaps was conducted for each of the four corners pedestrians crossed from to see if there were any differences in gap acceptance.

Rejected

To determine whether the rejected gaps were the same, both an independent-samples median test and Kruskal-Wallis test were conducted to determine whether the medians of the rejected gaps across the four crossing starting locations was the same and whether the distribution of rejected gaps across the four crossings starting locations was the same. Figure 10 below displays some count statistics of the rejected gaps and the null hypotheses and final outcomes of these tests.



Hypothesis Test Summary

	Null Hypothesis	Test	Sig.^{a,b}	Decision
1	The medians of GapRejected are the same across categories of PositionRejected.	Independent-Samples Median Test	.932	Retain the null hypothesis.
2	The distribution of GapRejected is the same across categories of PositionRejected.	Independent-Samples Kruskal-Wallis Test	.707	Retain the null hypothesis.

a. The significance level is .050.

b. Asymptotic significance is displayed.

Figure 10 – Rejected Gaps - Independent samples median and K-W test results and frequency counts

Median

Figure 11 below displays the independent-samples median test results. Analysis was conducted with a significance of 95% and alpha of 0.05. From this analysis, it was concluded that there was no significant difference in medians of rejected gaps between the four starting crossing locations.

Independent-Samples Median Test Summary

Total N	85
Median	2.560
Test Statistic	.438[a]
Degree Of Freedom	3
Asymptotic Sig.(2-sided test)	.932

a. Multiple comparisons are not performed because the overall test does not show significant differences across samples.

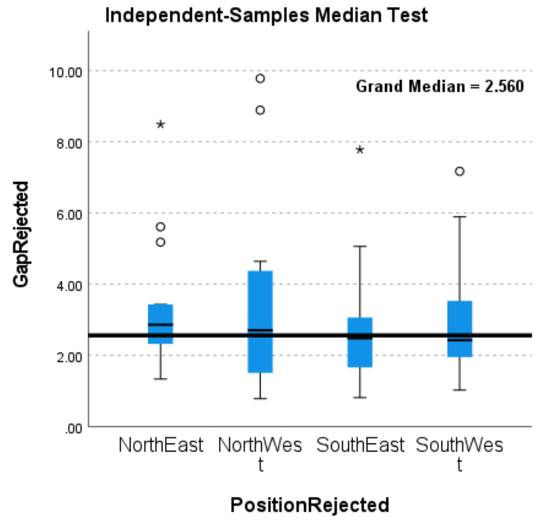


Figure 11 – Rejected Gaps - Independent samples median test for crossing locations

Kruskal-Wallis

Figure 12 below displays the independent-samples Kruskal-Wallis test results. Analysis was conducted with a significance of 95% and alpha of 0.05. From this analysis, it was concluded that there was no significant difference in rejected gap distributions between the four starting crossing locations.

Independent-Samples Kruskal-Wallis Test Summary

Total N	85
Test Statistic	1.393[a,b]
Degree Of Freedom	3
Asymptotic Sig.(2-sided test)	.707

a. The test statistic is adjusted for ties.

b. Multiple comparisons are not performed because the overall test does not show significant differences across samples.

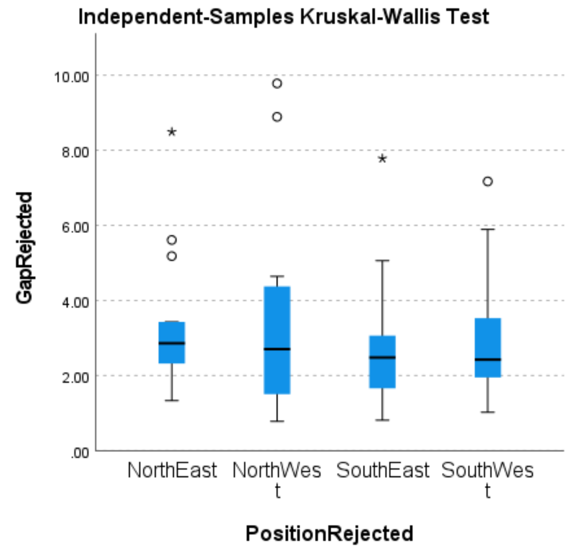
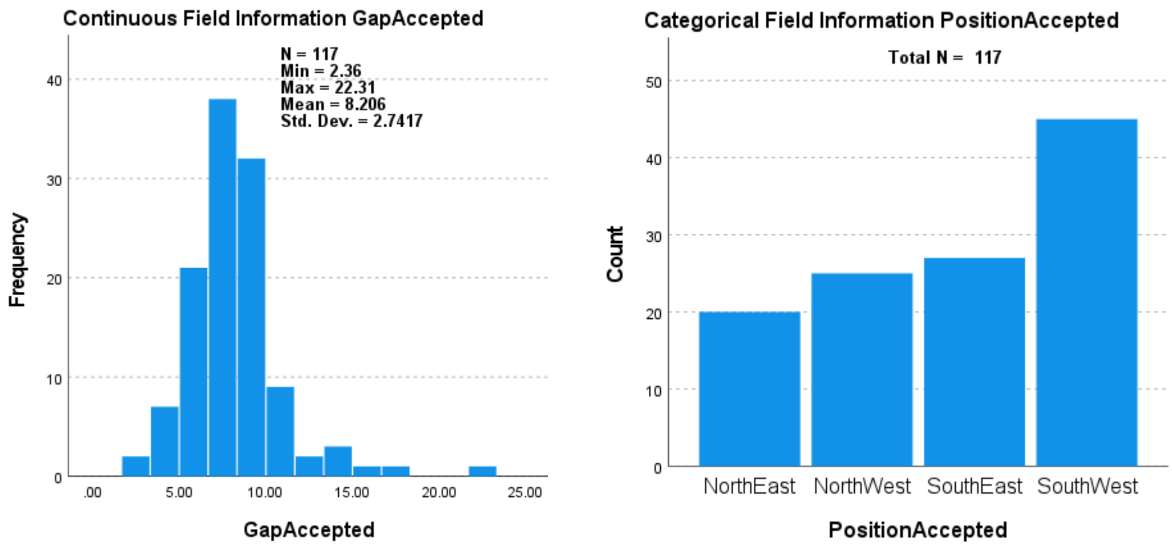


Figure 12 – Rejected Gaps - Independent samples K-W test for crossing locations

Accepted

To determine whether the accepted gaps were the same, both an independent-samples median test and Kruskal-Wallis test were conducted to determine whether the medians of the accepted gaps across the four crossing starting locations was the same and whether the distribution of accepted gaps across the four crossings starting locations was the same, respectively. Figure 13 below displays some count statistics of the accepted gaps and the null hypotheses and final outcomes of these tests.



Hypothesis Test Summary

	Null Hypothesis	Test	Sig.[a,b]	Decision
1	The medians of GapAccepted are the same across categories of PositionAccepted.	Independent-Samples Median Test	.415	Retain the null hypothesis.
2	The distribution of GapAccepted is the same across categories of PositionAccepted.	Independent-Samples Kruskal-Wallis Test	.220	Retain the null hypothesis.

a. The significance level is .050.

b. Asymptotic significance is displayed.

Figure 13 – Accepted Gaps - Independent samples median and K-S test results and frequency counts

Median

Figure 14 below displays the independent-samples median test results. Analysis was conducted with a significance of 95% and alpha of 0.05. From this analysis, it was concluded that there was no significant difference in medians of accepted gaps between the four starting crossing locations.

Independent-Samples Median Test Summary

Total N	117
Median	8.050
Test Statistic	2.851[a]
Degree Of Freedom	3
Asymptotic Sig.(2-sided test)	.415

a. Multiple comparisons are not performed because the overall test does not show significant differences across samples.

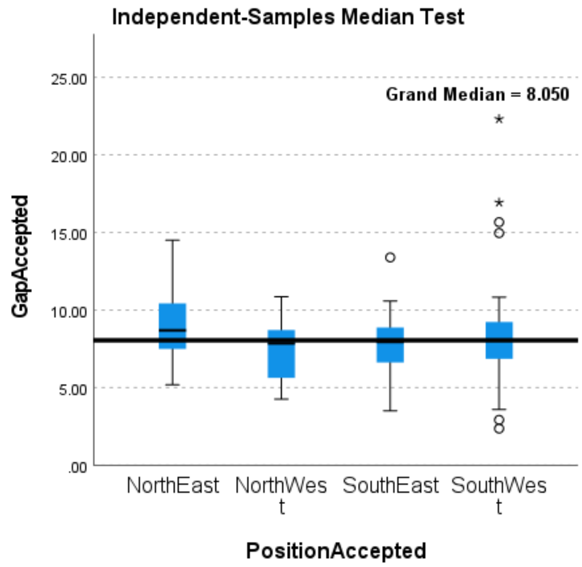


Figure 14 – Accepted Gaps - Independent samples median test for crossing locations

Kruskal-Wallis

Figure 15 below displays the independent-samples Kruskal-Wallis test results. Analysis was conducted with a significance of 95% and alpha of 0.05. From this analysis, it was concluded that there was no significant difference in accepted gap distributions between the four starting crossing locations.

Independent-Samples Kruskal-Wallis Test Summary

Total N	117
Test Statistic	4.419[a,b]
Degree Of Freedom	3
Asymptotic Sig.(2-sided test)	.220

a. The test statistic is adjusted for ties.

b. Multiple comparisons are not performed because the overall test does not show significant differences across samples.

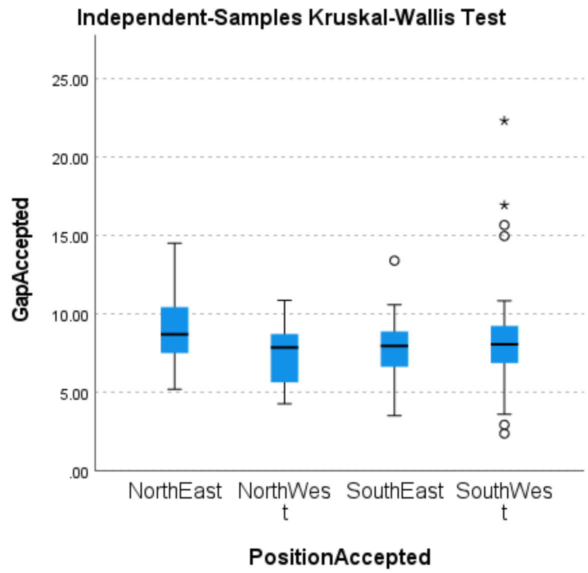


Figure 15 – Accepted Gaps – Independent samples K-W test

4.3.5 Vehicle Modelling

Since the analysis of the observed real-world shows that there was no significant difference in median and distribution of accepted and rejected gaps at the mid-block crosswalk of 1st Street S and Water Street, the entirety of the dataset could be used in constructing an empirical cumulative distribution function to represent vehicle gaps.

Empirical Distribution

A bin size of 0.2 seconds was determined in order to generate gaps that accurately reflected the empirical distribution to preserve the granularity of the data. Larger bins produced too low of a resolution of the distribution where generating gaps wouldn't be indicative of the actual distribution, whereas any finer resulted in bins that were all too similar in weight. Figure 16 below displays the histogram of the binned observed gaps and the cumulative distribution function (CDF) of the data.

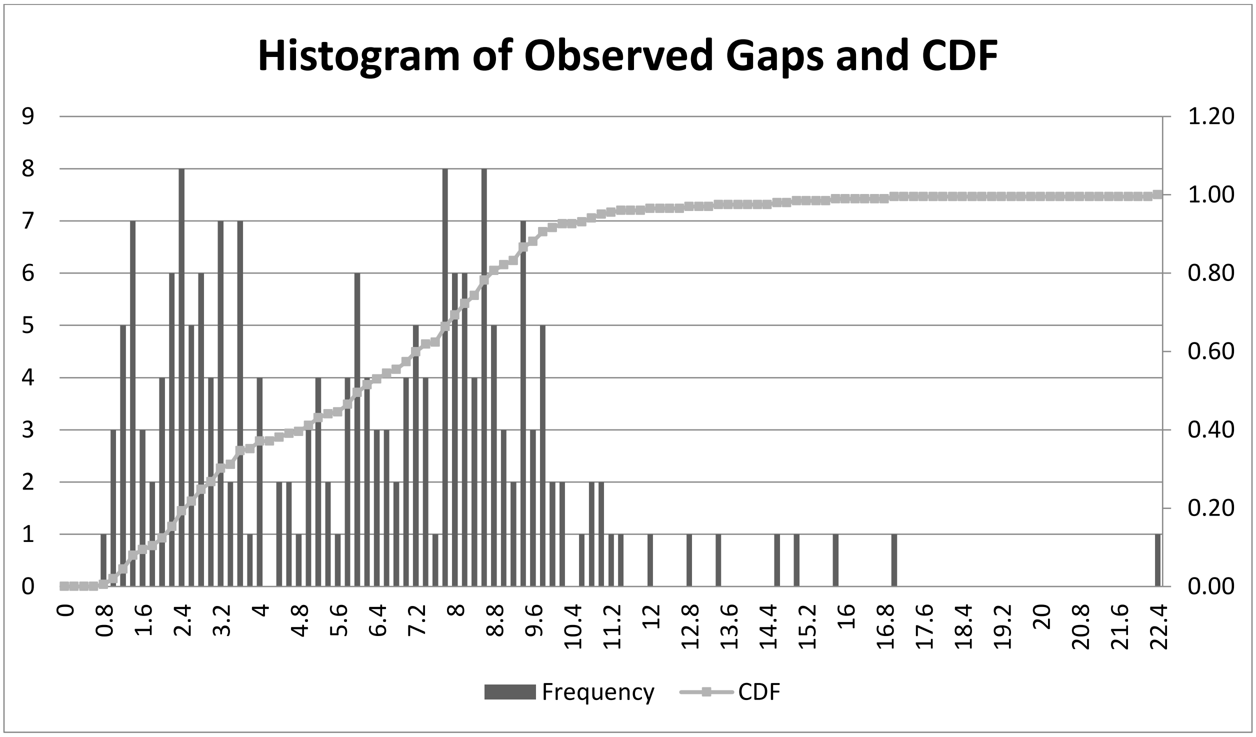


Figure 16 – Histogram of observed gaps and cumulative distribution function

This CDF was then used to generate random gaps within these 0.2 second bins. Gap generation was limited to producing gaps between 1 second and 15 seconds in order to avoid generating gaps that would certainly be rejected (less than 1 second) or accepted (greater than 15 seconds). The resulting CDF limited to gaps within 1 to 15 seconds represented 97.5% of the empirical data. In order to generate gaps, it was determined that the sample of gaps to be generated from the CDF would be 15 gaps long. Fewer gaps resulted in distributions that did not match the CDF well, and any more resulted in too many gaps for testing purposes, limiting the exposure to each generated gap. Gaps were generated randomly based on the weight of each 0.2 second bin of the CDF. Table 6 below shows a sample of generated gap data from the CDF, with the actual sample of generated gaps that would be used in the study highlighted in green.

Table 6 – Sample gap size generations and chosen generated gap set.

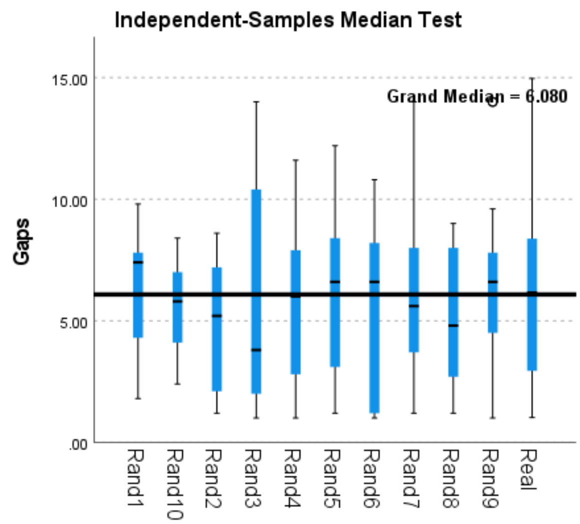
GAP #	1	2	3	4	5	6	**7**	8	9	10	*REAL DISTRIBUTION (1<X<15)*
1	*1.8*	*1.2*	*1*	*1*	*1.2*	*1*	1.2	*1.2*	*1*	*2.4*	
2	*2*	*1.4*	*1.4*	*1.2*	*1.4*	*1*	2	*1.4*	*2*	*2.4*	
3	*2.4*	*1.6*	*1.6*	*2*	*1.4*	*1*	2.8	*1.8*	*2.6*	*2.8*	
4	*3.8*	*1.8*	*2*	*2.4*	*1.6*	*1.2*	3.2	*2*	*3.8*	*3.6*	
5	*4.8*	*2.4*	*2*	*3.2*	*4.6*	*1.2*	4.2	*3.4*	*5.2*	*4.6*	
6	*6.8*	*4*	*2.8*	*5*	*4.8*	*2*	5.4	*3.8*	*5.4*	*5.6*	
7	*7*	*4.8*	*3.4*	*5.4*	*5.4*	*2.4*	5.4	*4.8*	*5.6*	*5.8*	
8	*7.4*	*5.2*	*3.8*	*6*	*6.6*	*6.6*	5.6	*4.8*	*6.6*	*5.8*	
9	*7.4*	*5.4*	*4.2*	*7*	*6.6*	*7*	6.2	*6.2*	*6.6*	*6.6*	
10	*7.4*	*6.6*	*6.6*	*7.2*	*8.2*	*7.8*	7	*7.6*	*7.4*	*6.8*	
11	*7.8*	*7*	*8.6*	*7.2*	*8.2*	*8.2*	7.8	*7.8*	*7.6*	*7*	
12	*7.8*	*7.4*	*12.2*	*8.6*	*8.6*	*8.2*	8.2	*8.2*	*8*	*7*	
13	*8.2*	*7.4*	*13.4*	*8.6*	*9.6*	*8.2*	9.6	*8.6*	*9.6*	*7.2*	
14	*8.4*	*7.6*	*14*	*8.6*	*10.8*	*8.6*	10.8	*8.6*	*14*	*8.2*	
15	*9.8*	*8.6*	*14*	*11.6*	*12.2*	*10.8*	14	*9*	*14*	*8.4*	
MEAN	6.19	4.83	6.07	5.67	6.08	5.01	6.23	5.28	6.63	5.61	5.93
MEDIAN	7.4	5.2	3.8	6	6.6	6.6	5.6	4.8	6.6	5.8	6.16
STD DEV	2.56	2.60	5.01	3.16	3.59	3.63	3.48	2.90	3.81	2.02	3.13
MIN	1.8	1.2	1	1	1.2	1	1.2	1.2	1	2.4	1.02
MAX	9.8	8.6	14	11.6	12.2	10.8	14	9	14	8.4	14.96
MEAN RANK	109.37	83.5	97.37	99.57	86.23	106.5	107.36	94.23	110.17	98.7	106.02
Z	-0.256	-1.455	-0.538	-0.392	-1.274	-0.066	-0.121	-0.745	-0.309	-0.45	
SIG (2 TAILED)	0.798	0.146	0.591	0.695	0.203	0.947	0.903	0.456	0.758	0.653	
Z	0.785	1.148	0.919	0.536	0.708	1.148	0.383	0.632	0.593	0.995	
SIG (2 TAILED)	0.569	0.143	0.367	0.936	0.698	0.143	0.999	0.82	0.873	0.275	

In determining which generated gaps best fit the empirical CDF, multiple tests were conducted. Table 6 above shows some descriptive statistics to capture the overall picture of each generated distribution. Furthermore, each randomly generated distribution was analyzed against the empirical CDF in an independent-samples median test to determine whether or not there were any differences, as shown in Figure 17 below.

Independent-Samples Median Test Summary

Total N	345
Median	6.080
Test Statistic	3.336[a]
Degree Of Freedom	10
Asymptotic Sig.(2-sided test)	.972

a. Multiple comparisons are not performed because the overall test does not show significant differences across samples.



Hypothesis Test Summary

	Null Hypothesis	Test	Sig.[a,b]	Decision
1	The medians of Gaps are the same across categories of Field.	Independent-Samples Median Test	.972	Retain the null hypothesis.

a. The significance level is .050.

b. Asymptotic significance is displayed.

Figure 17 – Indepedented samples median test between randomly generated gaps against real world distribution

Though there were no differences in the medians of each generated sample of data, the descriptive statistics helped in the selection of a randomly generated gap. Random distribution 7 was chosen for use in subject testing as it was no different than the median of the empirical gaps, but also because the range of the distribution was similar to the empirical results and it had very few repeating gaps unlike many of the other random distributions.

Chapter 5: Simulator Validation – Pedestrians in VR vs. Real World

The purpose of the benchmark test is to validate that the IVE developed is an accurate portrayal of real-world environments through 1) questionnaires asking participants about their experience with the virtual world and 2) comparing data collected during the real-world observation with data collected during the benchmark. Participants should feel that they are experiencing and interacting with the virtual world similarly to how they would in a real-world situation. The benchmark phase of this test will consist of subjects answering a pre-experiment test and a personality test, entering the virtual environment and conducting the experiment, and finally answering a post-experiment test. The pre-test questionnaire will consist of questions pertaining to their use of traffic facilities (what is their mode of transportation daily, do they ever consider using alternate methods of travel). When entering the virtual environment subjects will interact with various objects (vehicles passing, crossing signals, traffic signals). Finally, the post-test questionnaire will ask participants if their experience in the virtual world was comparable to real world experiences (did you feel you behaved differently, how so, compare your comfort to crossing in the virtual world vs that of the real world). The results from this experiment will be compared to those found in the real-world observations to determine whether pedestrians behave similarly at the midblock crossing in virtual reality as they do to the same one in the real world. The pre and post-test questionnaires can be found in Appendices A and B, respectively.

5.1 Experimental Design

5.1.1 Pilot testing

The pilot testing consisted of having participants, primarily undergraduate researchers, enter the virtual reality environment and interact with it. This phase of the experiment and the associated data from this experiment was conducted prior to full validation of the IVE and was not considered part of the overall experiment, but was intended for assuring that the virtual environment and associated equipment (headsets, EEG devices, smartwatch wearables) were all in working order before formal experimentation.

Performance metrics

- Stated observations and impressions of realism – basic feedback of the virtual environment were collected for understanding how the functionality of the virtual environment performed, whether subjects felt that the environment was realistic, whether certain aspects of the environment took them out of the experience, etc.
- Feedback of bugs, glitches, or other operational failures – feedback regarding any bugs or glitches the participants may have encountered in the environment that broke the subject's immersion or impeded their actions or behavior.

5.1.2 Marked Crosswalk

The first scenario to consider is the status quo of the crosswalk on 1st St S and Water St as depicted in Figure 18 below. This is a marked, high visibility crosswalk that crosses at a one-way intersection, but behaves nearly identical to a standard midblock crosswalk. This crosswalk sees a relatively large amount of foot traffic due to the many parking lots adjacent to Water Street that are used by workers and shoppers for accessing the downtown mall.

Figure 18 – One of the crosswalks contained in this study, this one is the one we will want to be conducting this study at 1st St S @ Water St (60)

This scenario consisted of the pedestrian entering the virtual environment and approaching the crosswalk a few steps from the curb. The pedestrian was be allowed to cross the road whenever they felt appropriate. Subjects were instructed to cross the road as they normally would when they felt comfortable doing so. The testing script real aloud to all participants can be found in Appendix C.

Performance metrics

Pre and post-test questionnaires will be conducted to understand pedestrian stated behaviors and preferences and can be compared to their actual behaviors in the virtual environment. This validation study was primarily focused on how the behavior of pedestrians compared between real-world and virtual environments and not what individual factors or perceptions influenced or correlated with pedestrian behavior in the IVE; therefore, survey data was only be reported (not statistically analyzed) and used for understanding anomalies in overall pedestrian crossing behavior.

The independent variable of consideration is the environment of the test: Real World or VR. There are four primary dependent variables that data is collected for: Accepted Gap Number, Gap Size, Crossing Speed, and Reaction to Last Vehicle. Detailed information for each of these variables is included in Table 7 below.

Table 7 – Variables in VR environment, interpretation, and method for measuring

Variable Type	Variable	Units	Interpretation	How it is Measured
Independent	**Environment**	Nominal	There are three environments that each subject will be exposed to: 1. As Built - modelled to be the same as the real-world environment 2. Flashing Beacons - Rapid Flashing Beacons are installed at the crosswalk 3. Phone App - the environment is identical to the As Built environment, with the inclusion of the CV midblock crossing phone app	The environment number is recorded
Dependent	**Accepted Gap No.**	Ordinal	The gap number that was accepted by the pedestrian for determining how many gaps they waited for before crossing to determine any correlation in wait time and environment.	Record the number of the accepted gap.
	Gap Size	*Seconds*	*The gap size the subject has accepted for crossing. Gap size is used for understanding when a pedestrian deems it is safe to cross the road.*	*Record the accepted gap size for each subject.*
	Crossing Speed	*Mph*	*Walking speeds will aid in the understanding and identification of a dart/dash movement, whether the pedestrian may have chosen a gap they are uncomfortable with, or whether the pedestrian feels anxious when crossing.*	*Average crossing speed is calculated by taking the total time spent crossing and dividing it by the distance across the roadway. Start up delay, or the time a subject spends standing still within the crosswalk, is subtracted from the total time spent crossing in order to prevent inaccurate crossing speeds.*
	Reaction to Last Vehicle	Directional / Yield Behavior	The pedestrian reaction to the last vehicle metric will indicate whether pedestrians waited for all vehicles to pass before crossing, whether vehicles yielded for the pedestrian, or whether the pedestrian chose a gap they felt acceptable for crossing. This behavior is indicative of pedestrian safety as well as comfort. Different interpretations can be drawn from this data as this is considered the pedestrians accepted gap. The gap size accepted can indicate that:	Record whether there was a vehicle approaching when the pedestrian began the crossing from both directions. Record whether the pedestrian waited for the vehicle to stop. If the pedestrian didn't wait, then this is the pedestrian's accepted gap.

As previously mentioned, for this experiment, two variables, italicized in the figure above, will be considered as the primary dependent variables for validating the efficacy of VR for studying crossing behavior as compared to real-world crossing behavior: Gap Size and Crossing Speed. Gap size is the primary dependent variable for consideration, as it is the standard for determining the behavior of pedestrians at midblock crossings as well as an indicator for perception of safety. Crossing speed is another highly valuable dependent variable because it indicates the safety of a pedestrian's movement across a crosswalk.

Accepted Gap Number and the Reaction to Last Vehicle are not considered for the VR vs Real-World analysis. Accepted Gap Number isn't considered because the distribution of gaps generated in VR follows a more granular structure as compared to the real-world observed gaps; therefore, the exposure to each of the 15 second gaps is higher than the distribution of 0.2 second gap bins as previously discussed in Section 4.4.5 and has a stronger bias to representing these larger bins of data. Reaction to Last Vehicle is not considered either as the VR environment does not control vehicle behavior as a pedestrian approaches and crosses the crosswalk as it does in the real-world. Normally, when a pedestrian begins to cross at an uncontrolled crossing, cars may slow down or yield for the pedestrian so they may cross which would be considered an instance where the pedestrian waits for a vehicle to stop. In the IVE for the as-built scenario, vehicles don't yield for the pedestrian unless the pedestrian is within their lane. This approach was done for multiple reasons:

- Determining whether or not a pedestrian was trying to communicate with approaching vehicles of their intent to cross is too arbitrary for controlling. Some pedestrians wave, others stand in place, some begin to cross and try to make eye contact to get a signal from approaching vehicles, etc.
- Determining whether or not a vehicle should stop for a pedestrian in the crosswalk depending on pedestrian position is also arbitrary, as some pedestrians like to stand entirely on the side of the road and others right at the start of the crosswalk, so identifying a fixed

point for the pedestrian to pass to have approaching vehicles yield for them was also arbitrary.

- Having vehicles stop for the pedestrian when they step into the crosswalk is unrealistic, some drivers will stop and some won't in real life and modelling this behavior in VR would add another layer of complexity to the study that would not only require a large sample size, but is also not representative of an accepted gap. When pedestrians wait for vehicles to yield for them, these gaps are neither considered rejected nor accepted and thus cannot be used for comparison between gap acceptance between real-world and VR environments.

Controls

Multiple factors were controlled in the virtual environment to limit the factors that may influence pedestrian crossing behavior, but also to replicate the real-world environment that was used for comparison analysis. There were two different types of identified controls: Dynamic Controls and Static Controls. Dynamic Controls refer to variables that are randomized for each subject trial, but are controlled within a set of boundaries as predetermined by the researcher so as to not inflict any bias on the dependent variables. Static Controls refer to variables that may normally be influencing environmental factors, but have been set to be constants for every trail so that the independent variable may be entirely isolated.

Table 8 – Controlled variables within VR environment

Control Type	Variable	Method	Reasoning
Dynamic Control	**Vehicle Gaps**	The gaps between vehicles will follow a randomized pattern from a predetermined distribution as decided upon by the researchers.	The distribution of gap times presented to the test subjects will follow the same distribution as the accepted gap time of as observed at the real-world crosswalk. This distribution will be determined from the cumulative distribution of real-world gap times. The sample of gaps will be randomized for each participant to avoid bias towards gaps based on exposure.

	Vehicle Types	Vehicle type and color will be randomized for each participant based off of a predetermined set of four vehicle types, all coupes.	Limit any bias of gap acceptance based on vehicle type and color based on exposure.
Static Control	**Vehicle Speeds**	Vehicle speeds will be restricted to 25 mph within the environment.	This is the posted speed limit along the corridor of Water St. Keeping all vehicles' speeds set at 25 mph will limit the variability in vehicle behaviors and possible randomization bias, allowing for completely replicable driver behaviors.
	Weather	Weather for each environment will be set to a clear, sunny day and will remain unchanged between tests	Reduce any possible changes in crossing behavior that may be induced due to weather conditions. Reduce any affects of weather on visibility of objects in environment.
	Starting Position	All pedestrians will start in the same position within the virtual environment at the northeast corner of the intersection, facing southbound at the crosswalk crossing Water Street, standing a few feet from the curb's edge.	Reduce any possible changes in crossing behavior based on perception of vehicles gaps, walking speed, etc.

5.2 Subject Recruitment

The explanation below was originally proposed for this dissertation as the method for recruiting an appropriate sample size for data analysis. Unfortunately, due to COVID, protocols for subject recruitment delayed the study by nearly a whole year and restricted the ability to recruit subjects on the timeline that was previously anticipated. Despite these restrictions, subject recruitment and testing was able to begin February 2nd, 2021 after receiving approval for in person subject testing at the ORCL and finished March 12th, 2021 with a total of 50 subjects having been recruited for testing. The previously proposed method for subject recruitment is left below for reference purposes. The email used for subject recruitment can be found in Appendix D and the Informed Consent Form signed by all participant who participated in this study can be found in Appendix E.

There are two factors of particular importance in this experiment that will be used to validate the virtual environment to the real-world environment: walking speed and gap acceptance. Walking speed is paramount as it reflects pedestrian movement in the virtual environment and is a direct indicator of behavior in the crosswalk. Gap acceptance is also paramount as it reflects the pedestrians perceived safety and will be used as an indicator of realism in the virtual environment.

To determine what sample size should be recruited.

To determine sample size, both walking speeds and gap acceptance data will be analyzed from the real-world environment to determine the standard deviations needed to determine sample size via the equation:

$$n=z2*22$$

Where:

n = sample size

z = z-score of confidence level

σ *= standard deviation*

ε *= margin of error*

The factor that has the largest needed sample size will be deemed as the sample we will aim to recruit.

Utilizing the second approach as described in the previous section regarding dataset constructions, 43.9% of the data recorded is deemed utilizable with a total of 420 recordings exactly identical to one another. Due to the lower number of recordings, some decisions will have to be made to determine what margin of error and confidence level should be chosen due to the variability in the standard deviation. As it stands, all of the crossing time has been analyzed for this dataset and with a standard deviation of .687595 seconds. With a margin of error of 10%, and a confidence level of 85%, 98 subjects will need to be recruited. Once all of the gap acceptance data has been recorded, it will be analyzed via the same method and a decision will be made as to how many subjects should be recruited.

5.3 Simulator Validation Results

This section of Chapter 5 presents the results of the VR experiment and compares these outcomes to the behavior of pedestrians in the real-world environment to validate the use of IVE technology for studying pedestrian behavior. As previously mentioned, this analysis looks at two major dependent variables: Gap Size and Speed.

5.3.1 Accepted Gap Size

Similarly shown in Chapter 4.4.4, the accepted and rejected gaps of the subjects in the As Built IVE are plotted against the # of gaps seen in the IVE. A total of 49 gaps were selected and 123 were rejected, for a grand total of 172 gaps. Though there were 50 subjects in this study, one of the gaps was removed due to data quality reasons, thus results are only shown for 49 subjects. Of these 49 subjects 24 were female and 26 were male. 24 (49%) of the 49 subjects were between 18 and 29 years old, 12 (24.5%) between 30 and 39, 4 (8.2%) between 40 and 49, 4 (8.2%) between 50 and 59, and 4 (8.2%) of 60 years or greater – one subject did not report their age.

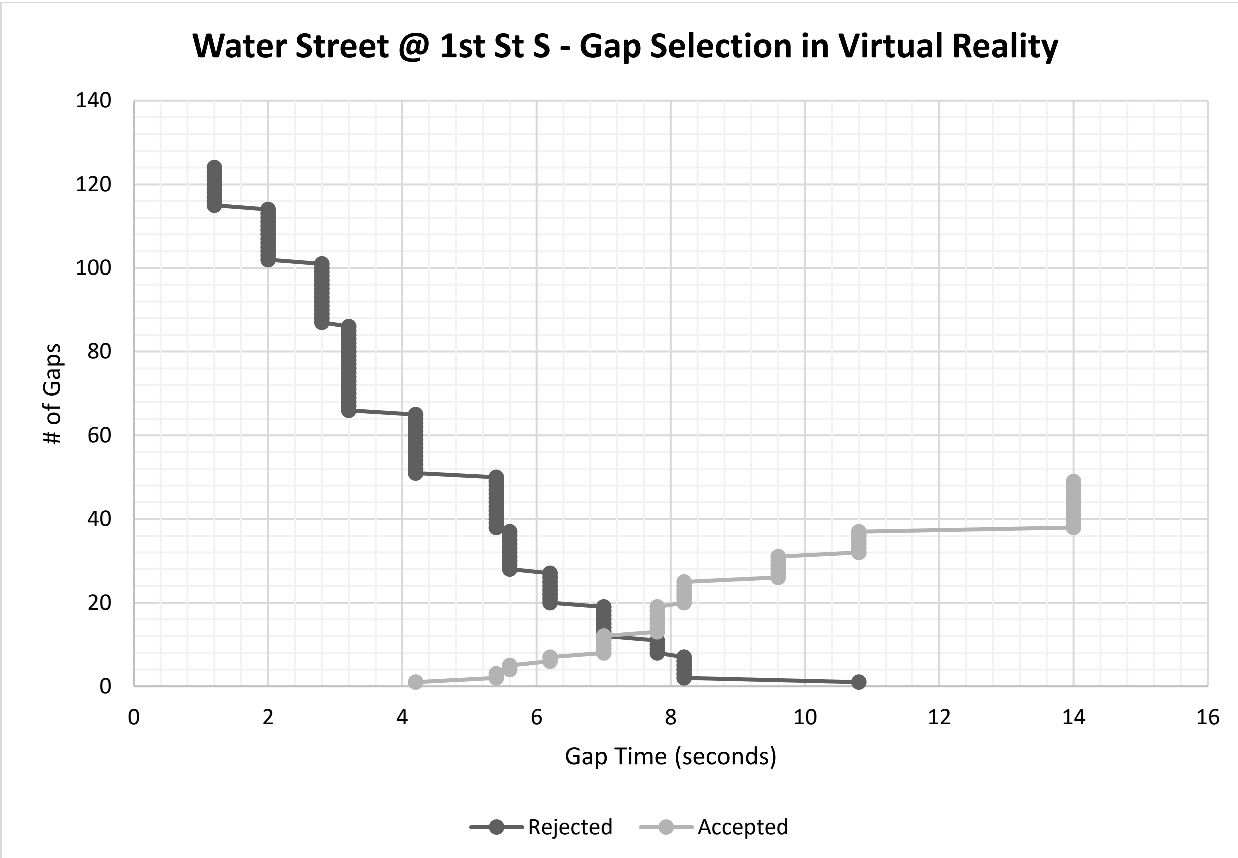
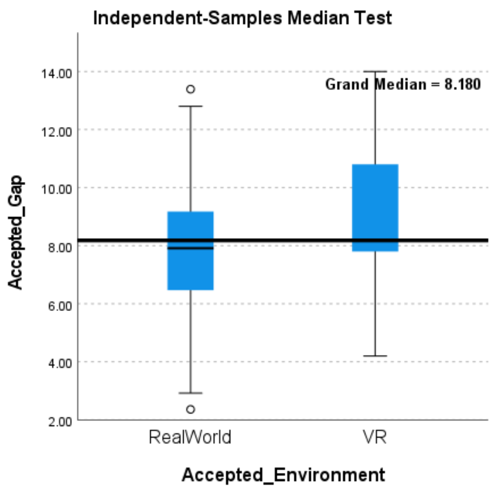


Figure 19 – Gap selection and critical gap of pedestrian crossing in VR environment

Figure 19 shows that the accepted and rejected gap distributions overlap at 7 seconds, indicating that 7 seconds is the critical gap time in which pedestrians decide to accept a gap, rather than reject it in the IVE. Compared to the real-world environment's critical gap time of 5.12 seconds, 7 seems much larger. To determine whether the accepted gap distributions between the real-world and VR environments are similar, an independent samples median test was conducted. The results of this test are shown in and Figure 20 below. It should be noted that the total of real-world gaps was reduced to 114 from 117, removing larger gaps that fall outside of the 1-15 second range that the gaps in VR were generated.



Hypothesis Test Summary

	Null Hypothesis	Test	Sig.[a,b]	Decision
1	The medians of Accepted_Gap are the same across categories of Accepted_Environment.	Independent-Samples Median Test	.078[c]	Retain the null hypothesis.
2	The distribution of Accepted_Gap is the same across categories of Accepted_Environment.	Independent-Samples Mann-Whitney U Test	.[d]	Unable to compute.
3	The distribution of Accepted_Gap is the same across categories of Accepted_Environment.	Independent-Samples Kolmogorov-Smirnov Test	.[e]	Unable to compute.
4	The distribution of Accepted_Gap is the same across categories of Accepted_Environment.	Independent-Samples Kruskal-Wallis Test	.003	Reject the null hypothesis.

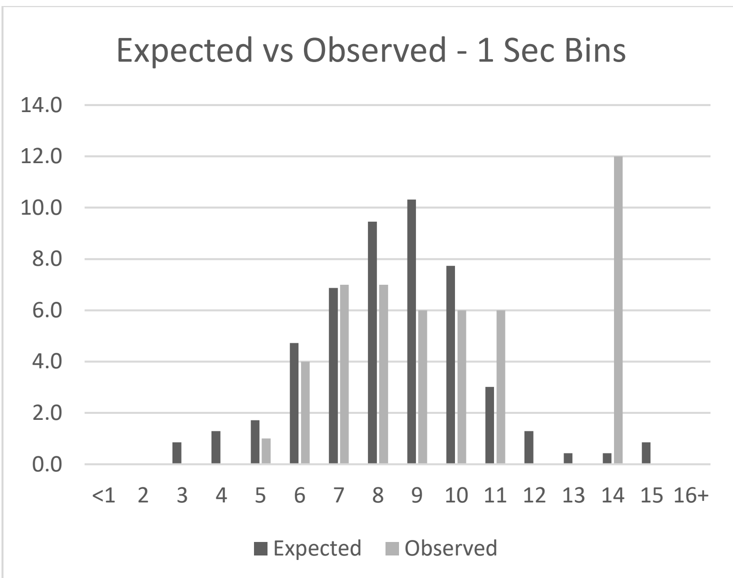
a. The significance level is .050.
b. Asymptotic significance is displayed.
c. Yates's Continuity Corrected Asymptotic Sig.
d. The group field does not have exactly two values.
e. The group field does not have exactly two values.

Figure 20 – Independent samples median test results between real world an VR environments

With respect to Figure 20 above, it is seen that the independent samples median test reports that the medians between the real-world and VR environments are not different; however, the significance statistic of .078 is borderline significant. The other appropriate test to evaluate here would be the Mann-Whitney U test because many of the values of the accepted gaps in VR were tied (the Kolmogorov-Smirnov test does not handle ties as well), but the output from SPSS indicates that it is unable to compute the significance value for this data set. In reanalyzing the data, and as will be discussed, this is because the distribution of the accepted gaps is heavily skewed to 14 second gaps. Looking at the ranges of the gaps as seen in Figure 20, the box plot of the VR accepted gaps shows the 75th quartile heavily favoring larger gap sizes.

Chi-Square Analysis

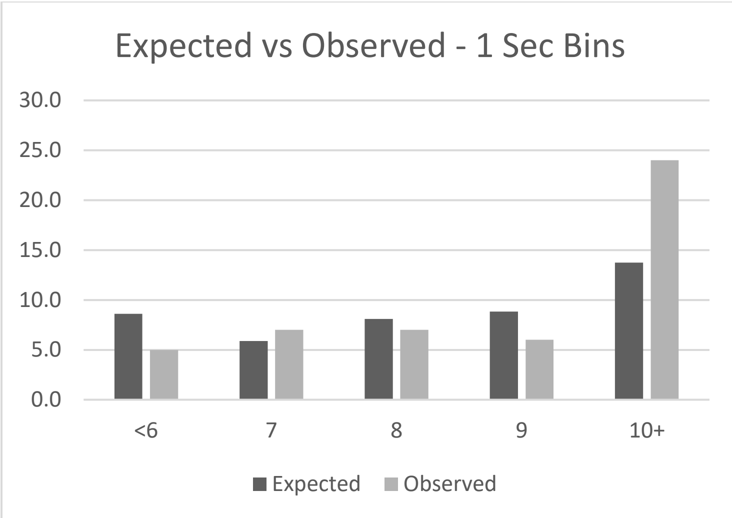
To determine whether accepted gap size distributions were similar, a chi-squared analysis was deemed the most appropriate approach for determining statistical significance between the two datasets. Chi-square analysis was deemed the most appropriate approach because the real-world data had already been reduced to a cumulative distribution for modelling vehicle arrivals, thus, the VR data results are weighted heavily to their discrete value. Binning the VR data negates the weight on the discrete values chosen to represent the real-world gap data and shifts that weight to a bin range in which the real-world data can be categorized into as well so that they may be compared as shown in Figure 21 below.



Bin	Expected	Observed	(O-E)^2/E
<1	0.0	0.0	
2	0.0	0.0	
3	0.9	0.0	
4	1.3	0.0	0.9
5	1.7	1.0	1.3
6	4.7	4.0	0.3
7	6.9	7.0	0.1
8	9.5	7.0	0.0
9	10.3	6.0	0.6
10	7.7	6.0	1.8
11	3.0	6.0	0.4
12	1.3	0.0	3.0
13	0.4	0.0	1.3
14	0.4	12.0	0.4
15	0.9	0.0	311.5
16+	0.0	0.0	
		χ Sum	321.54
		$\chi 2$	21.92

Figure 21 – 1 second bins for chi-square analysis

In only one instance did consolidating the 1 second bins meet the chi-squared statistic without violating the assumptions of the analysis. While this method produced a statistically significant value, the distribution of these accepted gaps is far too consolidated and is not indicative of any distribution of the data whatsoever. This consolidated dataset is shown below in Figure 22.



Bin	Expected	Observed	(O-E)^2/E
<6	8.6	5.0	1.5
7	5.9	7.0	0.2
8	8.1	7.0	0.2
9	8.8	6.0	0.9
10+	13.8	24.0	7.6
		χ Sum	10.41
		$\chi 2$	11.14

Figure 22 – 1 second bin for chi-square analysis combined

Equation X below was used for determining the appropriate bin size for the data.

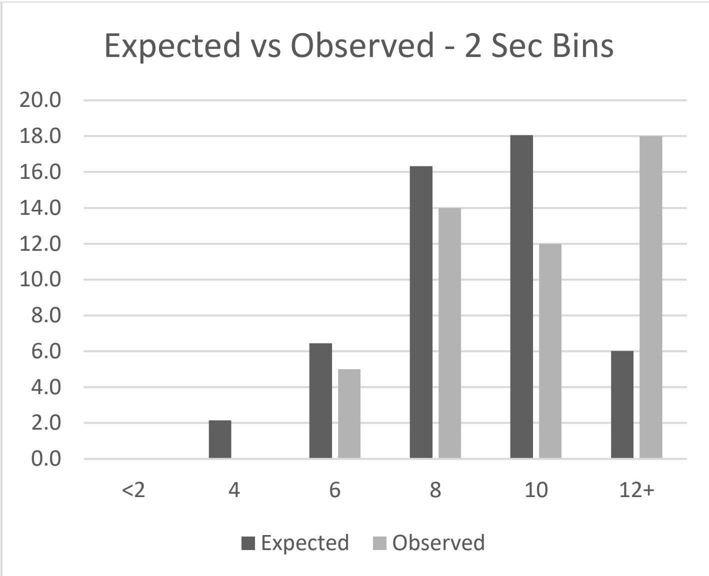
$$I = \frac{14}{1 + 3.22 * \log(n)}$$

Where:

I = interval for bin size

n = population size of group used for calculating expected results

From this equation, a bin size of 1.84, or, rounding up, 2 seconds was determined. The results of the 2 second bin with some consolidation of the larger bins is shown in Figure 23 below and does not meet the chi-squared statistic.

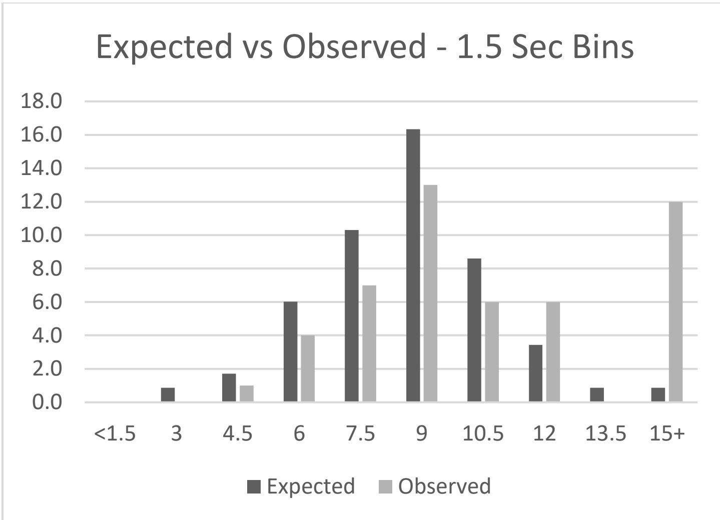


Bin	Expected	Observed	(O-E)^2/E
<2	0.0	0.0	
4	2.1	0.0	2.1
6	6.4	5.0	0.3
8	16.3	14.0	0.3
10	18.1	12.0	2.0
12+	6.0	18.0	23.9
		χ Sum	28.70
		χ2	11.14

Figure 23– 2 second bins for chi-square analysis condensed

Further consolidation of the 2 second bins to meet the chi-squared statistic would require consolidating the 10 and 12+ bins to reduce the chi-squared absolute difference shown in the 12+ second bin of Figure 23 and would violate the assumptions of the chi-squared test with 25% of the bins (the 4 second bin) having and expected value under 5.

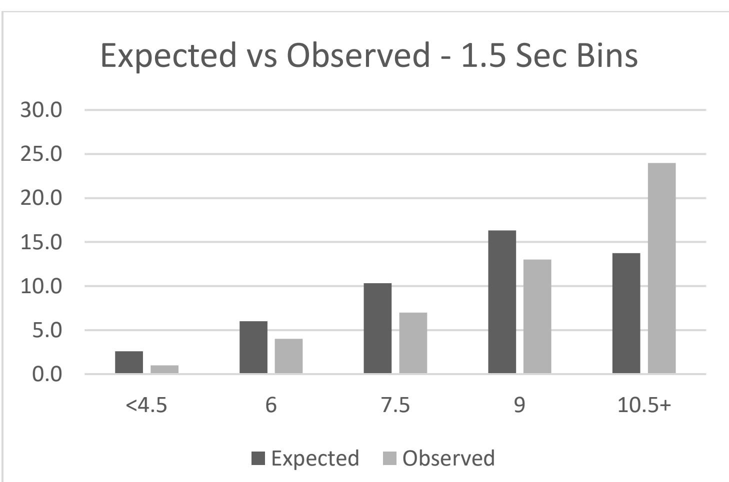
The use of 2 second bins could not meet the chi-squared statistic, regardless of how the bins were consolidated, thus, 1.5 second bins were considered for analysis to increase the granularity of the data but remain close to ideal interval of 1.84 seconds. Figure 24 below presents the data of the 1.5 second bins.



Bin	Expected	Observed	(O-E)^2/E
<1.5	0.0	0.0	
3	0.9	0.0	0.9
4.5	1.7	1.0	0.3
6	6.0	4.0	0.7
7.5	10.3	7.0	1.1
9	16.3	13.0	0.7
10.5	8.6	6.0	0.8
12	3.4	6.0	1.9
13.5	0.9	0.0	0.9
15+	0.9	12.0	144.4
		χ Sum	151.50
		χ2	17.53

Figure 24 –1.51 second bins for chi-square analysis

This approach best shows the distributions of accepted gap sizes between the expected and observed data sets; however, like the 1 second bins, in only one instance did consolidating the 1.5 second bins meet the chi-squared statistic without violating the assumptions of the analysis. The distribution of these accepted gaps was far too consolidated and is not indicative of any distribution of the data whatsoever. This consolidation is shown in Figure 25 below.



Bin	Expected	Observed	(O-E)^2/E
<4.5	2.6	1.0	1.5
6	6.0	4.0	0.2
7.5	10.3	7.0	0.2
9	16.3	13.0	0.9
10.5+	13.8	24.0	7.6
		χ Sum	11.02
		χ2	11.14

Figure 25 – 1 second bins for chi-square analysis comdensed

Looking at these figures, it becomes clearly apparent that the reasoning for why many of these distributions have to be consolidated into bins with large values, creating distributions of near exponential growth in gap distribution is because of the large number of subjects in the VR environment who accepted the 14 second gap. Of the 49 subjects, 12 of them had accepted the singular, and largest gap of the fifteen gaps randomly presented to each subject and explains the skew of the boxplot presented in Figure 20.

This skew in the data led to a re-review of the video footage for the subjects who accepted the 14 second gaps. In doing so, it was found that 5 of these 12 subjects had a very similar experience in which they entered the crosswalk into the opposing traffic lane in which no vehicles were approaching, expected cars to yield to them, and observed that no cars were going to yield for them so they waited in the middle of the road until a large enough gap would arrive (which would be the 14 second gap) and then crossed. This behavior is not very realistic as, typically, approaching vehicles would yield for the pedestrian in the crosswalk, as is stat law in Virginia, and even if one didn't yield, the likelihood of many vehicles not yielding is even lower. It was determined that this condition was to be reassessed for all instances across the whole dataset, not limited to just the 14 second gaps. Across the entirety of the dataset, 9 of the 49 subjects experienced a similar situation. Table 9 below provides the participant number, some demographic information, and some of the post-test questionnaire responses that offer some insight into what was happening in these situations.

Table 9 – Survey resposnes and demographics for 9 subjects who experienced unrealistic crossing scenarios

Participant No.	Sex	Age	How immersed were you in the virtual environment experience?	How realistic was the vehicle traffic in the virtual environment?	Did the traffic seem responsive to your actions in the virtual environment?	Do you feel more or less compelled to observe the "rules of the road" while walking in the virtual environment compared to walking in real life?	How realistic was your sense of risk in the virtual environment?
1	Male	28	5	4	5	3	3
7	Male	20	5	3	5	3	4
8	Male	20	5	4	4	5	4
10	Female	30	5	4	5	2	3
11	Male	26	5	2	5	1	2
19	Female	18	4	2	3	2	3
37	Male	DNA	4	3	4	5	2
43	Male	19	3	1	5	2	2
44	Female	66	5	4	4	3	3

From this table, it could be inferred that survey responses varied the regarding the realism of the vehicle traffic, how compelled subjects were to follow road rules, and how realistic their sense of risk was in the VR environment and that nearly all of these subjects were under 30 years of age. Furthermore, nearly all of the subjects felt immersed in the environment. Vehicle responsiveness is helpful and shown to be agreed upon that it was indeed responsive, however these responses may be influenced by the other alternative environments in which vehicles and pedestrians interact different through technology.

One possible interpretation of these survey responses could be that subjects felt that the vehicle traffic was not realistic because the vehicles didn’t stop for them when they attempted to cross the road. Another is that subjects’ perception of risk in the IVE may not have been as realistic, thus, they were willing to cross into the opposing lane of traffic to wait out a gap to cross in. Table 10 below provides some of the individual statistics regarding their behavior in the As-Built IVE and what occurred during their test.

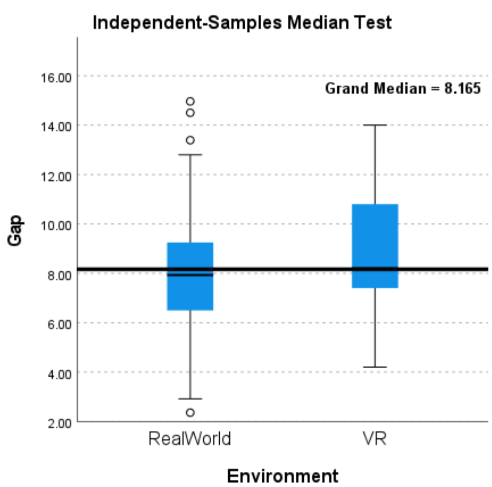
Table 10 – Crossing behavior in VR for 9 subjects who experienced unrealistic scenarios in VR and explanation of experience

Participant No.	Order No.	Accepted Gap No.	Accepted Gap No.	Accepted Gap Size	Start Up Delay in Crosswalk	Average Crossing Speed	What Happened During Test
1	3	4	1	14	6.9	3.82	Subject starts to walk into crosswalk and stops in opposing lane, creeps along crosswalk until 14 second gap appears.
7	3	5	3	6.2	9.86	3.21	Subject goes halfway into crosswalk and stops in opposing lane, cars don't stop, then crosses during 5.4 second gap.
8	1	9	0	14	22.43	2.16	Subject starts to walk into crosswalk and stops in opposing lane, creeps along crosswalk until 14 second gap appears.
10	1	3	0	14	5.18	2.59	Subject starts to cross into crosswalk during second gap, cars don’t stop so subject waits in opposing lane, then waits again for a long time until 14 second gap
11	3	4	1	8.2	6.87	1.78	Subject starts to cross, then the gap the subject is crossing for doesn't yield, so subject waits mid crosswalk in opposing lane for the next car to pass to cross.
19	2	4	1	10.8	6.6	2.64	Subject starts to cross, then waits in opposing lane for vehicles to stop but they don't, then crosses once there is a gap.
37	1	3	3	14	3.15	2.25	Subject starts crossing at second gap, notices car coming down hill and doesn't trust it to stop so subject waits for it to pass in opposing lane, and then takes 14 second gap.
43	1	2	1	7	2.9	2.73	Subject starts to cross, stops in opposing lane for car to yield, crosses after vehicle doesn't yield and passes crosswalk.
45	3	7	2	14	19.61	3.56	Subject creeps into the crosswalk early in flow of traffic, but no cars yield for her, so she waits in opposing lane until 14 second gap and then crosses.

Based on the results from the chi-squared analyses, skew in accepted gap distribution, and unrealistic observed behavior for these 9 participants, it was determined that these subjects’ data be removed from the data set and the data set be reanalyzed.

5.3.2 Accepted Gap Size – Adjusted

The results of the independent samples median test for the adjusted dataset are shown below in Figure 26. Previously, the significance in this median test was .078, which has now shifted to .358, indicating that the removal of these unrealistic observations has led to further conclusion that the two datasets are similar. Furthermore, the Mann-Whitney U test is now able to be computed by SPSS after removal of some of the larger gap sizes, reducing the skew as seen before. This analysis does show that there is a significant difference in between in the median between the two datasets, which is still most likely due to the fact that there is still a large number of data points in the 14 second gap bin. Figure 26 below also shows the box plot data for this independent samples median test. The removal of five of the twelve 14 second accepted gap sizes and fixed some of the skew in the box plot data, though, has not removed it entirely. Overall, though, the removal of these 9 subjects' data has provided better results for the independent samples median test.



Hypothesis Test Summary

	Null Hypothesis	Test	Sig.^{a,b}	Decision
1	The medians of Gap are the same across categories of Environment.	Independent-Samples Median Test	.358^{c}	Retain the null hypothesis.
2	The distribution of Gap is the same across categories of Environment.	Independent-Samples Mann-Whitney U Test	.046	Reject the null hypothesis.
3	The distribution of Gap is the same across categories of Environment.	Independent-Samples Kolmogorov-Smirnov Test	.023	Reject the null hypothesis.
4	The distribution of Gap is the same across categories of Environment.	Independent-Samples Kruskal-Wallis Test	.046	Reject the null hypothesis.

a. The significance level is .050.

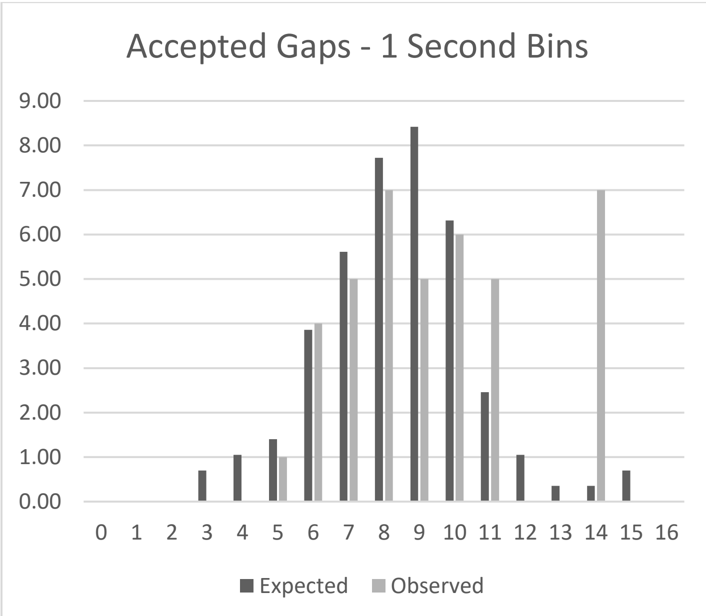
b. Asymptotic significance is displayed.

c. Yates's Continuity Corrected Asymptotic Sig.

Figure 26 – Independent samples mediant test beween real world and VR environments

Chi-Square Analysis

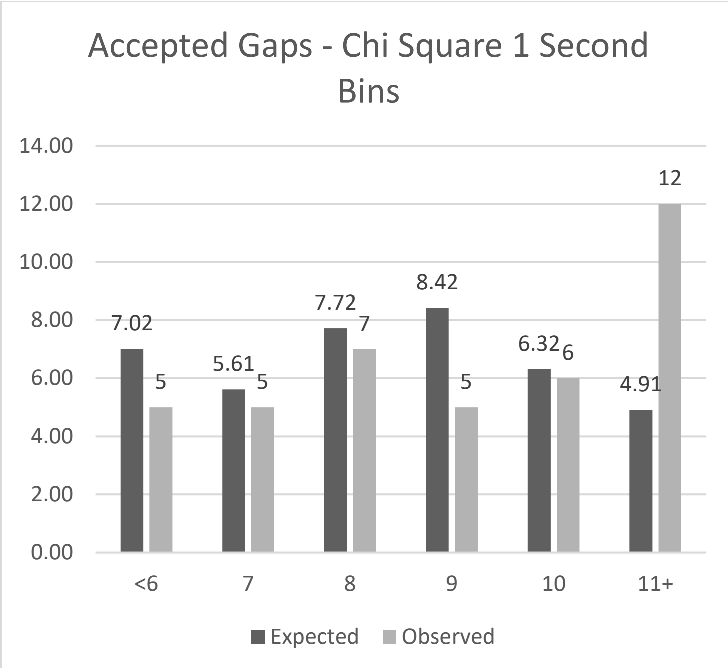
The chi-square analysis was reconducted with the new 40 subject data set. The results of this study for 1 second, unconsolidated bins, is shown in Figure 27 below.



Bin	Expected	Observed	(O-E)^2/E
<1	0.0	0.0	
2	0.0	0.0	
3	0.7	0.0	0.7
4	1.1	0.0	1.1
5	1.4	1.0	0.1
6	3.9	4.0	0.0
7	5.6	5.0	0.1
8	7.7	7.0	0.1
9	8.4	5.0	1.4
10	6.3	6.0	0.0
11	2.5	5.0	2.6
12	1.1	0.0	1.1
13	0.4	0.0	0.4
14	0.4	7.0	126.0
15	0.7	0.0	0.7
16+	0.0	0.0	
		χ Sum	134.16
		χ2	23.34

Figure 27– 1 second bins for chi-square analysis

As previously, unconsolidated, this test fails to meet the chi-square test assumptions. The skew in the 14 second gaps bin isn't as large, but still remains. Further analyses were conducted based on the interval size previously calculated as 1.83 in Chapter 5.3.1 for 2 second and 1.5 second bins; however, none of these analyses managed to meet the chi-square assumptions prior to meeting the chi-square statistic. One analysis did though, and met it using 1 second consolidated bins as shown in Figure 28 below.



Bin	Expected	Observed	(O-E)^2/E
<6	7.0	5.0	0.6
7	5.6	5.0	0.1
8	7.7	7.0	0.1
9	8.4	5.0	1.4
10	6.3	6.0	0.0
11+	4.9	12.0	10.2
		χ Sum	12.35
		χ2	12.83

Figure 28– 1 second bins for chi-square analysis condensed

While this analysis does not necessarily show the distribution of data as nicely as the unconsolidated 1 second binned data, it met all chi-squared assumptions and the statistic with six bins, the largest number of bins to be significant in this analysis.

5.3.3 Crossing Speed

Analysis Methods Discussion

Crossing speeds will be analyzed with the same approach as accepted gap sizes were – first as a full 49 subject data set, then as the adjusted 40 subject data set. Multiple approaches were taken to analyze crossing speed for validation between the IVE and real-world environments.

This first method considered was constructing a linear model of crossing speed and its relationship with accepted gap size to fit the real-world data and then analyzing how this model fit the VR data – the null hypothesis being that the model would fit both data sets and, thus, validating crossing speeds in the As-Built IVE. This method did not work, as a model could not be fit to the real-world data first: the residuals of the data set did not follow any pattern for linear fit, not did any linear model come close to representing the data in any way. To possibly correct for this, two transformations were considered: square root and natural log, in the hopes that the residuals of the data would be compressed enough to form some sort of correlation. This method also did not work, as the residuals for both transformations did not follow any correlations.

The second approach take was to conduct a median split of the data to compare the upper and lower splits of crossing speeds against on another for each environment – real-world and VR – and determine whether there is a relative difference in upper and lower mean split speeds between each environment that could be used to validate crossing behavior. The first step to this approach was to split the real-world data about the median and compare the upper and lower splits to determine whether there is a significant difference in the means, then determine the difference in the mean which would be compared against the mean difference between the VR median splits. Similar to the previously described approach, it was found that there was no significant difference in the means of the upper and lower median splits of the real-world data, thus, this method also could not be used. The calculations and outputs for both of these methods are shown in Appendix F.

Since neither of these methods could be used for validating crossing speeds in the real-world and VR environments based on model fitting or relative median split differences, the last approach considered was to conduct an independent samples t-test to determine whether or not there were any differences in the mean for crossing speed.

Table 11 – Independent samples t-test statistics and results

Group Statistics

	Environment	N	Mean	Std. Deviation	Std. Error Mean
Speed	0	114	3.3324	.66667	.06244
	1	49	3.3914	.77224	.11032

Independent Samples Test

		Levene's Test for Equality of Variances		t-test for Equality of Means						
									95% Confidence Interval of the Difference	
		F	Sig.	t	df	Sig. (2-tailed)	Mean Difference	Std. Error Difference	Lower	Upper
Speed	Equal variances assumed	3.659	.058	-.493	161	.623	-.05894	.11954	-.29501	.17714
	Equal variances not assumed			-.465	80.183	.643	-.05894	.12676	-.31120	.19332

Table 11 above shows that there was not a significant difference in crossing speed means between the real-world and VR environments. Furthermore, the Levene's test shows that there is no significant difference in the variance of the data set.

Table 12 – Independent samples t-test effect sizes

Independent Samples Effect Sizes

		Standardizer[a]	Point Estimate	95% Confidence Interval	
				Lower	Upper
Speed	Cohen's d	.69981	-.084	-.419	.251
	Hedges' correction	.70309	-.084	-.417	.250
	Glass's delta	.77224	-.076	-.411	.259

a. The denominator used in estimating the effect sizes.
Cohen's d uses the pooled standard deviation.
Hedges' correction uses the pooled standard deviation, plus a correction factor.
Glass's delta uses the sample standard deviation of the control group.

The estimated effects size for difference in VR and real-world crossing speeds is shown in Table 12 above. As shown, there is a nearly no effect on crossing speeds when switching between real-world and VR data, thus, it could be validated that subjects cross in the VR IVE similarly to the real-world; however, this data needs to be reanalyzed based off of the adjusted sample size previously discussed.

5.3.4 Crossing Speed – Adjusted

The independent samples t-test for the adjusted subject pool of 40 subjects is shown in Table 13 below.

Table 13– Independent samples t-test statistics and results

Group Statistics

	Environment	N	Mean	Std. Deviation	Std. Error Mean
Speed	0	114	3.3324	.66667	.06244
	1	40	3.5183	.71428	.11294

Independent Samples Test

		Levene's Test for Equality of Variances		t-test for Equality of Means						
									95% Confidence Interval of the Difference	
		F	Sig.	t	df	Sig. (2-tailed)	Mean Difference	Std. Error Difference	Lower	Upper
Speed	Equal variances assumed	1.446	.231	-1.489	152	.138	-.18588	.12482	-.43249	.06072
	Equal variances not assumed			-1.440	64.408	.155	-.18588	.12905	-.44366	.07189

Based on this analysis with the adjusted data set, there is still no significant difference in the means of crossing speeds between the as-built VR IVE and real-world environments. Furthermore, the Levene's test shows that there is no significant difference in the variance of the data set.

Table 14– Independent samples t-test effect sizes

Independent Samples Effect Sizes

		Standardizer[a]	Point Estimate	95% Confidence Interval	
				Lower	Upper
Speed	Cohen's d	.67920	-.274	-.635	.088
	Hedges' correction	.68258	-.272	-.632	.088
	Glass's delta	.71428	-.260	-.623	.106

a. The denominator used in estimating the effect sizes.
Cohen's d uses the pooled standard deviation.
Hedges' correction uses the pooled standard deviation, plus a correction factor.
Glass's delta uses the sample standard deviation of the control group.

Table 14 above re-illustrates the estimated effect size of crossing speeds when switching from real-world to VR environments. The reported effect sizes are smaller than they were with the 49 subject data set, still indicating that the use of VR had no effect on the average crossing speed of subjects, further validating that crossing speed behavior in VR is similar to real-world behavior.

5.3.5 Survey Data

The post-experiment survey data is presented in Table 15 below. Negative (1 and 2) and Positive (4 and 5) Likert scale responses have been compiled for the sake of simplicity in reading the results.

Table 15– Overview of survey results including all responses

Question	Negative (1-2)	Neutral (3)	Positive (4-5)	# Responses
How aware were you of events occurring in the real world around you while performing the assigned tasks in the virtual environment?	51.0%	18.4%	30.6%	49
How responsive was the environment to actions that you performed?	0.0%	8.0%	92.0%	50
How immersed were you in the virtual environment experience?	0.0%	6.0%	94.0%	50
Did the virtual environment feel appropriately to scale?	0.0%	4.0%	96.0%	50

To what extent did your experiences in the virtual environment seem consistent with your real-world experiences of crossing a street?	2.0%	12.0%	86.0%	50
How realistic was your sense of movement inside the virtual environment?	2.0%	6.0%	92.0%	50
How realistic was your sense of walking speed inside the virtual environment?	0.0%	8.0%	92.0%	50
How distracting were the controllers in your hands?	6.0%	14.0%	80.0%	50
How realistic was the vehicle traffic in the virtual environment?	10.0%	36.0%	54.0%	50
Did the traffic seem responsive to your actions in the virtual environment?	2.0%	12.0%	86.0%	50
Do you feel more or less compelled to observe the "rules of the road" while walking in the virtual environment compared to walking in real life?	18.0%	64.0%	18.0%	50
How realistic was your sense of risk in the virtual environment?	12.0%	30.0%	58.0%	50
How safe did you feel crossing the road using the mobile phone application?	16.0%	20.0%	56.0%	50
How safe did you feel crossing the road using the rapid flashing beacons?	0.0%	4.0%	90.0%	50
How safe did you feel crossing the road without additional safety devices?	32.7%	40.8%	26.5%	49

5.4 Simulator Validation Discussion

Goal I of this dissertation was to prove the feasibility of utilizing VR technology as a tool for conducting real-world experimentation of pedestrian's behavior. Chapter 5 provided a validation analysis between real-world and virtual behavior in an IVE that was modelled on a one-to-one scale of a real-world, high-risk environment. To prove the validation of the virtual environment, two variables were considered as the main indicators of pedestrian behavior and safety: accepted gap size and average crossing speed.

Accepted Gaps

Accepted gap size is indicative of pedestrians' perception of safety at a crosswalk and is arguably the standard for determining the safety of an uncontrolled crossing aside from crash analyses. It represents the threshold of risk pedestrians are will to accept before rejecting a gap. To validate an IVE, it is paramount that this risk be similar to the real-world environment it is modelled after so that further analysis of the crossing location in VR could be used for real-world practice.

To validate the IVE to the real-world environment, chi-square distributions were used for determining whether the distribution of accepted gaps was similar between the two environments. There was a likeness of distributions between real-world and VR chi-square analyses, and some distributions of the data were statistically similar.

It is believed that, in analyzing pedestrian gap acceptance, VR and real-world environments are similar and the use of IVEs for studying pedestrian safety at uncontrolled crossings is a valid approach. There are a few drawbacks to this study, though, that would need to be improved so that more accurate results could be drawn. The primary factor considered as the cause for some skew in the gap acceptance of the IVE towards larger gap sizes is the vehicle behavior. As previously discussed in Chapter 5, vehicle behavior was modelled so as to avoid making arbitrary decisions as to when vehicles would stop for pedestrians attempting to cross at the crossing and instead, never stopped for the pedestrian unless the subject was in the lane of the vehicle itself. While both of the distributions of gap acceptance only analyzed data in which the pedestrian crossed before a vehicle yielded for them, there are significant differences between the real-world and IVEs that may have led pedestrians to not trust vehicular traffic as much in the IVE.

Firstly, there are no drivers visible in the approaching vehicles for the pedestrians to visually make eye contact with or communicate with; therefore, there is a level of trust or accountability in the driver to slow down for the pedestrian should they cross in front of the vehicle. Second, though the distribution of gap sizes presented to the pedestrians is modelled directly after real-world gap sizes based off of the cumulative distribution of this data, there is still an overexposure of 14 second gaps to subjects in the IVE as compared to the real-world data. This becomes apparent when considering the statistical significance between the accepted gap sizes when looking at the independent median tests and the Mann Whitney U test, where it is clear that the medians of accepted gap sizes of the real-world and IVE are similar, but the ranks of these data as produced by the Mann Whitney U test are not and are skewed because of the IVE's 14 second gap acceptance rate. Furthermore, a larger sample size for analysis would also prove ideal as there is still a loss in data from the 50 subject data set used in this study. While a 50 subject data pool is still larger than many previous tests using VR technology to study pedestrian behavior, a larger sample size would help in providing a better distribution to compare against the real world data and would be less susceptible to changes in variance.

Despite these limitations, subjects still reported very positive results in the post test survey shown in Chapter 5.3.5. 94% of subjects felt they were immersed in the environment, 86% felt that their experience in the IVE was consistent with their real-world experiences, and 92% felt that their sense of movement and walking speed was realistic in the IVE. With respect to risk, 58% reported that their sense of risk was realistic, though, 30% reported it was somewhat realistic and only 12% reported that it was unrealistic. Comparing these results with the 54% of subjects who felt that the traffic was realistic in the IVE, it can be inferred that the realism of the traffic was most likely the cause for any changes in perception of risk, but that, generally, the IVE was well received and considered realistic, further validating the use of IVE for studying pedestrian safety at uncontrolled crossings.

Crossing Speed

Average crossing speeds are indicative of the safety of a pedestrian's crossing. Uncontrolled crossings experience variances in crossing speeds based off of pedestrians' behavior and perception of risk – pedestrians may walk across a road slowly with caution or may dart across the road to reduce their exposure to oncoming traffic, the latter approach being considered a sign of unsafe crossing behavior in research.

To validate the IVE to the real-world environment, multiple approaches were taken to show the determine whether there was a difference in crossing speeds and, thus, crossing safety. While many of the first approaches failed to sample the real-world data accurately, the independent samples t-test did show that the means of crossing speeds in the IVE and real-world environments were not statistically significant from one another. Furthermore, the Levene's test shows that there was no significant difference in the variance between the crossing speeds in the two environments either, validating that pedestrians crossed with the same behavior and risk in the IVE as they did in the real-world.

Comparing these results with the survey responses in Chapter 5.3.5, 92% of subjects felt that their sense of movement and their sense of walking speed inside the IVE was realistic, further validating the efficacy of the use of IVEs.

Chapter 6: Safety Analysis of Pedestrians in VR with Alternative Technologies

6.1 Alternative Design Testing

The purpose of the alternative design phase was to understand pedestrian behavior, acceptance, and compliance with different roadway designs, infrastructure, and technology as compared to the as-built design at the midblock crossing at Water St and 1st St S. This portion of the experiment tested subject's behavior with two new forms of technology at the Water St and 1st St S midblock crossing: (1) Subjects crossed with the inclusion of a rapid flashing beacon at the midblock crossing (2) Subjects crossed with the inclusion of the cellular midblock crossing application as discussed in detail in Chapter 3. The participants took a pre-experiment questionnaire and personality test (the same as in the validation test) and then experienced the alternative scenarios in the IVE. Pedestrian speeds, accelerations, head movements, field of vision, and physiological data were be collected as well as behavior (did they cross at the crosswalk or near it, did they wait longer for a vehicle to stop, did they dart into the road without waiting). After the experiment, participants took a post-test questionnaire to assess their perceptions of the alternative technologies and perceived safety. Data collected from this experiment was directly compared to that of the validation study described in Chapter 5.1.2 to understand any changes in observed and perceived safety.

Performance metrics

In addition to the performance metrics included in the validation study in Chapter 5.2.2, the following performance metrics were be used for the alternative design/technology testing:

Table 16 – New dependent variable included in VR testing with alternative technology

Variable Type	Variable	Units	Interpretation	How it is Measured
Dependent	**Technology Acceptance**	Nominal	The use of the alternative technology will help determine whether subjects are more willing to use alternative safety features to aid in their crossing.	Record whether alternative technology was activated or not

Pre and post-test questionnaires were conducted to understand pedestrian stated behaviors and preferences and can be compared to their actual behaviors in the virtual environment. This safety analysis was primarily focused on how the behavior of pedestrians changed with the inclusion of alternative safety technologies and not what individual factors or perceptions influenced or correlated with pedestrian behavior in the IVE; therefore, survey data was only reported (not statistically analyzed) and used for understanding anomalies in overall pedestrian crossing behavior.

6.2 Experimental Design

6.2.1 Rapid Flashing Beacon

Within the last five years, many midblock crossings around the university grounds have been upgraded with rectangular rapid flashing beacons (RFBs). Figure 29 below shows one of such crosswalks along University Avenue by Little Johns sub shop.

Figure 29 Midblock crosswalk with RFBs along University Ave (61)

The beacons work by pedestrians approaching the crosswalk from either side of the road, pressing a button that initiates the yellow flashing pattern, and crossing when approaching vehicles have stopped.

This scenario will consist of the pedestrian entering the virtual environment and approaching the crosswalk heading westbound on Water Street on the Northside of the road. The pedestrian should be allowed to cross the road whenever they feel appropriate, whether it be at the crosswalk or not; subjects will simply be instructed to cross the road. Pedestrians should be able to interact with the RFB by pressing the button located on the sign pole to initiate the flashers on the beacon. Vehicles approaching the crosswalk should react accordingly to the pedestrian:

- If the pedestrian is at the crosswalk attempting to cross and uses the RFB, they should yield for the pedestrian immediately.
- If the pedestrian is at the crosswalk waiting for a gap without pressing the RFB, cars should not stop.
- If the pedestrian is in the crosswalk, vehicles should yield for the pedestrian.

6.2.2 Mobile Phone Application

The last scenario for study incorporated the capability for use of the midblock crossing application discussed in Chapter 3. This application was designed to allow users to use their cellphone to send in vehicle messages to approaching vehicles to alert them of the pedestrian's intent to cross at the midblock crosswalk. The application does not allow users to send these types of messages when they are not near a crosswalk, so they cannot spam approaching messages to approaching drivers.

For the purposes of this study, pedestrians had a cellphone in their hand while in the virtual environment (they will have a controller in their hand in real life, but will see a phone when they look at their hand). On the screen of the phone, a simplified user interface was shown to make operations easier to understand for the pedestrian. There were two screens that the pedestrians saw on the mobile phone during testing had they interacted with it fully during their crossing.

- The first screen of the mobile phone application asked the pedestrian if they wished to cross the crosswalk and provided a button labeled "Yes" for use if the subject wished to use the application.
- Should the pedestrian answer "Yes", a new screen appeared that stated "Your request is being broadcast". The pedestrian was free to cross the crosswalk and vehicles yielded when subjects responded by pressing the "Yes" button.

The user interface design is included below in Figure 30.

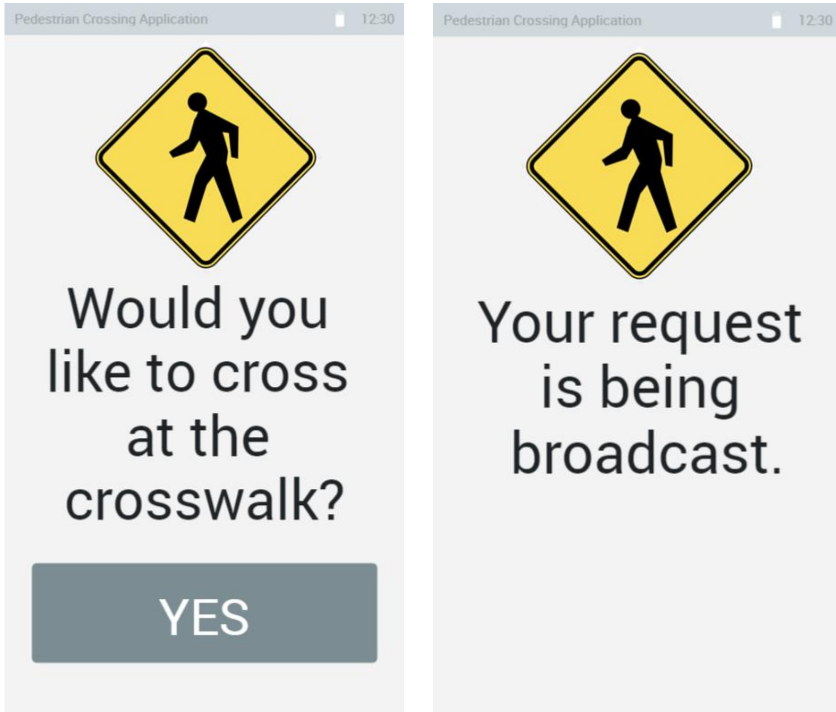


Figure 30 User interface layout for two screens pedestrians could interact with while in the IVE

Vehicle behavior with the mobile phone application.

- If the pedestrian was at the crosswalk attempting to cross and uses the application, they should yield for the pedestrian immediately.
- If the pedestrian was at the crosswalk waiting for a gap without using the app, vehicles did not yield for the pedestrian.
- If the pedestrian was in the crosswalk in the approaching lane of vehicles, vehicles yielded for the pedestrian.

6.3 Results

The results presented in this analysis are based off of a few adjustments made to the datasets of the VR environments:

- The As-Built environment consists of the same 40 subject group that was used in Chapter 5, instead of the 49-subject dataset (for full 49-subject dataset calculations, refer to Appendices G and H). This was done to preserve the continuity of data use and to remove any data that might skew the differences in subject behavior in the IVEs.
- The Flashing Beacon and Phone App IVEs have been reduced as well by removing subjects with poor data that couldn't be used for analysis as well as subjects who did not use the alternative technologies. The breakdown for data removal is as follows:
  - Flashing Beacon – 16% data removed, total of ***42 subjects retained***
    - 3 subjects' data was removed for poor data collection reasons, representing 6% of the data
    - 5 subjects' data was removed because they did not use the flashing beacons, representing 10% of the data
  - Phone App – 14% of data removed, total of ***43 subjects retained***
    - 3 subjects' data was removed for poor data collection reasons, representing 6% of the data
    - 4 subjects' data was removed because they did not use the phone app, representing 8% of the data

6.3.1 Correlations

First, a Spearman correlation was conducted to determine if there were any correlations between the independent variable of the VR tests, the environment, and the dependent variables of the experiment: the accepted gap number, accepted gap size, crossing speed, and reaction to last vehicle. Variable coding for this analysis is as follows:

Table 17 – Variable coding for statistical analysis in calculations

Variable	Code
As Built	1
Flashing Beacons	2
Phone App	3

Spearman correlation was chosen because the environment, accepted gap number, and vehicle model variables are both nominal and ordinal sets of data and a Spearman's correlation is designed to analyze these data sets in a monotonic relationship – where two variables change together, but not at a constant rate – unlike a Pearson correlation which can only evaluate two continuous variables as they proportionally change together. Table 18 below provides the correlation coefficient and the significance of the correlations between the independent variable, the environment, against the four dependent variables.

Table 18 – Spearman correlation coefficients and significance values between alternative technology environments

		Accepted Gap No.	Gap Size	Crossing Speed	Reaction to Last Vehicle
Environment	Correlation Coefficient	***-.629****	***-.255****	***-.431****	***.698****
	Sig. (2-tailed)	***0.000***	***0.004***	***0.000***	***0.000***

*****. Correlation is significant at the 0.01 level (2-tailed).***

**. Correlation is significant at the 0.05 level (2-tailed).*

As shown in above, there are significant differences between the environments for all four of the dependent variables. Accepted gap number, accepted gap size, and crossing speed all had negative correlations with the environment variables, indicating that as the environment switches between the As Built to the Flashing Beacons and Phone App, gaps are accepted sooner, accepted gap size decreased, and crossing speed decreased.

There was a strong positive correlation between the environments and the reaction to the last vehicle which is categorized as (1) crossed during gap and (2) waited for approaching vehicle to stop. This variable is expected to be positive because the As Built environment vehicles never yielded for the pedestrian before they were crossing, but only when they were in the lane of traffic, in which case the reaction to the last vehicle would still be coded as "1". With the alternative technologies, most subjects waited for traffic to yield before crossing, though not all did.

Furthermore, in order to determine whether the dynamic constants in the experiment, the order of which each environment was experienced and the randomized vehicle models presented to the subjects, had a significant impact on subject behavior, these constants were treated as variables in the Spearman correlation. As shown in Tables 19 and 20 below, neither one of these dynamic constants had a significant impact on subject behavior nor was there any significant bias in the randomization of the order of vehicle model in any of the environments.

Table 19 – Spearman correlation coefficients and significanve values with respect to dynamic control variable "Order"

		Environment	Accepted Gap No.	Vehicle Model	Gap Size	Crossing Speed	Reaction to Last Vehicle
Order	Correlation Coefficient	0.048	-0.076	-0.040	0.001	0.117	0.058
	Sig. (2-tailed)	0.593	0.402	0.656	0.992	0.194	0.522

*****. Correlation is significant at the 0.01 level (2-tailed).***

**. Correlation is significant at the 0.05 level (2-tailed).*

Table 20– Spearman correlation coefficients and significanve values with respect to dynamic control variable "Vehilce Model"

		Environment	Order	Accepted Gap No.	Gap Size	Crossing Speed	Reaction to Last Vehicle
Vehicle Model	Correlation Coefficient	0.132	-0.040	-0.150	-0.119	0.035	0.120
	Sig. (2-tailed)	0.142	0.656	0.096	0.186	0.700	0.184

*****. Correlation is significant at the 0.01 level (2-tailed).***

**. Correlation is significant at the 0.05 level (2-tailed).*

6.3.2 Accepted Gaps

Descriptive statistics of the accepted gap sizes for each environment are provided in Table 21 below. The mean values presented are recorded gap times in seconds.

Table 21 – Descriptive statistics for three VR environments' accepted gaps

Descriptives

Gap

	N	Mean	Std. Deviation	Std. Error	95% Confidence Interval for Mean		Minimum	Maximum
					Lower Bound	Upper Bound		
1.00	40	9.1400	2.78170	.43983	8.2504	10.0296	4.20	14.00
2.00	42	6.6476	3.08349	.47579	5.6867	7.6085	1.20	14.00
3.00	43	6.9721	3.18257	.48534	5.9926	7.9515	1.20	14.00
Total	125	7.5568	3.19613	.28587	6.9910	8.1226	1.20	14.00

Repeated Measures ANOVA

A repeated measures ANOVA test was conducted to determine whether there were significant differences in gap size selection for each participant. The dataset was reduced to a total of 33 subjects who had complete and uncompromised data and used each of the technologies in the alternative technology environments. The descriptive statistics as well as the results of the repeated measures ANOVA are shown in Table 22 below.

Table 22 – Repeated measures ANOVA descriptive statistsics between three VR environments and within subject effects for accepted gap sizes

Descriptive Statistics

	Mean	Std. Deviation	N
AsBuilt	8.7818	2.77280	33
FlashingBeacons	6.8545	2.79431	33
PhoneApp	6.9394	3.39687	33

Tests of Within-Subjects Effects

Measure: MEASURE_1

Source		Type III Sum of Squares	df	Mean Square	F	Sig.	Partial Eta Squared
Environment	Sphericity Assumed	78.277	2	39.139	4.462	.015	.122
	Greenhouse-Geisser	78.277	1.924	40.680	4.462	.017	.122
	Huynh-Feldt	78.277	2.000	39.139	4.462	.015	.122
	Lower-bound	78.277	1.000	78.277	4.462	.043	.122
Error(Environment)	Sphericity Assumed	561.403	64	8.772			
	Greenhouse-Geisser	561.403	61.574	9.117			
	Huynh-Feldt	561.403	64.000	8.772			
	Lower-bound	561.403	32.000	17.544			

The results of the repeated measures ANOVA show that there is a significant difference in accepted gap sizes between the three environments within-subjects. To determine which environments differed from one-another, a pairwise comparison was also conducted utilizing a Bonferroni correction to account for repeated analyses being conducted on the data sets to minimize Type I error. This analysis is shown below in Table 23.

Table 23 – Pairwise comparisons between VR environment gap acceptance

Pairwise Comparisons

Measure: MEASURE_1

(I) Environment	(J) Environment	Mean Difference (I-J)	Std. Error	Sig.[b]	95% Confidence Interval for Difference[b]	
					Lower Bound	Upper Bound
1	2	1.927*	.688	.026	.190	3.664
	3	1.842*	.697	.038	.082	3.602
2	1	-1.927*	.688	.026	-3.664	-.190
	3	-.085	.798	1.000	-2.101	1.931
3	1	-1.842*	.697	.038	-3.602	-.082
	2	.085	.798	1.000	-1.931	2.101

Based on estimated marginal means

*. The mean difference is significant at the .05 level.

b. Adjustment for multiple comparisons: Bonferroni.

As seen in Table 23 above, there was a significant difference in accepted gap size between the As-Built environment when compared to the Flashing Beacons and Phone App environments; however, there was no significant difference in accepted gap size between the Flashing Beacons and Phone App environments. This analysis further confirms that subjects behave similarly in the Flashing Beacons and Phone App environments and differently with alternative technologies than in the As-Built condition.

Paired Means T-Test

Paired t-tests were also conducted to discern differences in accepted gap size between the As-Built environment and the alternatives separately. This was done for two reasons: (1) to determine the effect size of each of these alternatives and (2) to look at the full datasets for each paired comparison without reduction from having to have all three datasets reduced to the same subjects. This process yielded 36 paired comparisons between the As-Built and Flashing Beacons environments and 35 paired comparisons between the As-Built and the Phone App environments.

As Built vs Flashing beacon

The descriptive statistics and results of the paired t-test are shown in Table 24 below.

Table 24 – Independent means paired t-test for gap acceptance between As Built and Flashing Beacons

Paired Samples Statistics

		Mean	N	Std. Deviation	Std. Error Mean
Pair 1	AsBuilt	8.8111	36	2.66016	.44336
	FlashingBeacons	6.5833	36	2.87029	.47838

Paired Samples Test

		Paired Differences Mean	Std. Deviation	Std. Error Mean	95% Confidence Interval of the Difference Lower	Upper	t	df	Sig. (2-tailed)
Pair 1	AsBuilt - FlashingBeacons	2.22778	3.95435	.65906	.88982	3.56574	3.380	35	.002

From this analysis, it can be further confirmed that there is a significant difference in accepted gap size between the As-Built and Flashing Beacons environment. Table 25 below shows that the estimated effect size is .563, indicating a moderate effect on accepted gap size. Again, this is expected as the As-Built scenario was weighted towards larger gap sizes, whereas in the alternative technologies, subjects almost always selected the first or second gap to cross during.

Table 25– Independent means paired t-test for gap acceptance between As Built and Flashing Beacons effect sizes

Paired Samples Effect Sizes

			Standardizer[a]	Point Estimate	95% Confidence Interval Lower	Upper
Pair 1	AsBuilt - FlashingBeacons	Cohen's d	3.95435	.563	.208	.912
		Hedges' correction	3.99736	.557	.206	.902

a. The denominator used in estimating the effect sizes.
Cohen's d uses the sample standard deviation of the mean difference.
Hedges' correction uses the sample standard deviation of the mean difference, plus a correction factor.

As Built vs Phone App

The descriptive statistics and results of the paired t-test are shown in Table 26 below.

Table 26– Independent means paired t-test for gap acceptance between As Built and Phone Application

Paired Samples Statistics

		Mean	N	Std. Deviation	Std. Error Mean
Pair 1	AsBuilt	8.8629	35	2.71457	.45885
	PhoneApp	7.0057	35	3.37098	.56980

Paired Samples Test

		Paired Differences					t	df	Sig. (2-tailed)
					95% Confidence Interval of the Difference				
		Mean	Std. Deviation	Std. Error Mean	Lower	Upper			
Pair 1	AsBuilt - PhoneApp	1.85714	3.91605	.66193	.51193	3.20235	2.806	34	.008

From this analysis, it can be further confirmed that there is a significant difference in accepted gap size between the As-Built and Phone App environment. Table 27 below shows that the estimated effect size is .474, indicating a nearly moderate effect on accepted gap size. Again, this is expected as the As-Built scenario was weighted towards larger gap sizes, whereas in the alternative technologies, subjects almost always selected the first or second gap to cross during.

Table 27– Independent means paired t-test for gap acceptance between As Built and Phone App effect sizes

Paired Samples Effect Sizes

			Standardizer[a]	Point Estimate	95% Confidence Interval	
					Lower	Upper
Pair 1	AsBuilt - PhoneApp	Cohen's d	3.91605	.474	.121	.821
		Hedges' correction	3.95992	.469	.120	.812

a. The denominator used in estimating the effect sizes.
Cohen's d uses the sample standard deviation of the mean difference.
Hedges' correction uses the sample standard deviation of the mean difference, plus a correction factor.

This effect size is similar to what we see in the Flashing Beacons environment, though it is a little smaller. Variance in the effect size could be attributed to gap size exposure during the first or second gaps; while the correlation matrix showed that accepted gap size wasn't correlated with gap order, that was for the entirety of the study including the As-Built scenario and may be slightly different in this particular analysis.

6.3.3 Crossing Speeds

Descriptive statistics of the crossing speeds for each environment are provided in Table 28 below. The mean values presented are average crossing speeds in miles per hour.

Table 28 – Descriptive statistics for three VR enviornments' crossing speeds

Descriptives

Speed

	N	Mean	Std. Deviation	Std. Error	95% Confidence Interval for Mean Lower Bound	95% Confidence Interval for Mean Upper Bound	Minimum	Maximum
1.00	40	3.5363	.72427	.11452	3.3047	3.7680	2.19	5.19
2.00	42	3.0163	.43375	.06693	2.8811	3.1514	2.23	4.49
3.00	43	2.8446	.50403	.07686	2.6895	2.9997	2.03	4.46
Total	125	3.1236	.63173	.05650	3.0118	3.2355	2.03	5.19

Repeated Measures ANOVA

A repeated measures ANOVA test was conducted to determine whether there were significant differences in crossing speeds for each participant in each environment. The dataset was reduced to a total of 33 subjects who had complete and uncompromised data and used each of the technologies in the alternative technology environments. The descriptive statistics as well as the results of the repeated measures ANOVA are shown in Table 29 below.

Table 29 – Repeated Measures ANOVA descriptive statistics and within subject effects for crossing speeds

Descriptive Statistics

	Mean	Std. Deviation	N
AsBuilt	3.6482	.72732	33
FlashingBeacon	3.0557	.46035	33
PhoneApp	2.9013	.49969	33

Tests of Within-Subjects Effects

Measure: MEASURE_1

Source		Type III Sum of Squares	df	Mean Square	F	Sig.	Partial Eta Squared
Environment	Sphericity Assumed	10.260	2	5.130	27.250	.000	.460
	Greenhouse-Geisser	10.260	1.537	6.674	27.250	.000	.460
	Huynh-Feldt	10.260	1.600	6.413	27.250	.000	.460
	Lower-bound	10.260	1.000	10.260	27.250	.000	.460
Error(Environment)	Sphericity Assumed	12.049	64	.188			
	Greenhouse-Geisser	12.049	49.198	.245			
	Huynh-Feldt	12.049	51.195	.235			
	Lower-bound	12.049	32.000	.377			

The results of the repeated measures ANOVA show that there is a significant difference in crossing speeds between the three environments within-subjects. To determine which environments differed from one-another, a pairwise comparison was also conducted utilizing a Bonferroni correction to account for repeated analyses being conducted on the data sets to minimize Type I error. This analysis is shown below in Table 30.

Table 30 – Repeated Measures ANOVA pairwise comparisons between three VR environments

Pairwise Comparisons

Measure: MEASURE_1

(I) Environment	(J) Environment	Mean Difference (I-J)	Std. Error	Sig.[b]	95% Confidence Interval for Difference[b]	
					Lower Bound	Upper Bound
1	2	.592*	.116	.000	.300	.885
	3	.747*	.125	.000	.432	1.062
2	1	-.592*	.116	.000	-.885	-.300
	3	.154	.073	.123	-.029	.338
3	1	-.747*	.125	.000	-1.062	-.432
	2	-.154	.073	.123	-.338	.029

Based on estimated marginal means

*. The mean difference is significant at the .05 level.

b. Adjustment for multiple comparisons: Bonferroni.

As seen in Table 30 above, there was a significant difference in crossing speed between the As-Built environment when compared to the Flashing Beacons and Phone App environments; however, there was no significant difference in crossing speeds between the Flashing Beacons and Phone App environments. This analysis further confirms that subjects behave similarly in the Flashing Beacons and Phone App environments and differently with alternative technologies as compared to the As-Built condition.

Paired Means T-Test

Similar to the accepted gap size analysis, paired t-tests were also conducted to discern differences in crossing speeds between the As-Built environment and the alternatives separately. This was done for two reasons: (1) to determine the effect size of each of these alternatives and (2) to look at the full datasets for each paired comparison without reduction from having to have all three datasets reduced to the same subjects. This process yielded 36 paired comparisons between the As-Built and Flashing Beacons environments and 35 paired comparisons between the As-Built and the Phone App environments.

As Built vs Flashing Beacon

The descriptive statistics and results of the paired t-test are shown in Table 31 below.

Table 31– Independent means paired t-test for crossing speeds between As Built and Flashing Beacons

Paired Samples Statistics

		Mean	N	Std. Deviation	Std. Error Mean
Pair 1	AsBuilt	3.5967	36	.72410	.12068
	FlashingBeacon	3.0457	36	.44352	.07392

Paired Samples Test

		Paired Differences							
		Mean	Std. Deviation	Std. Error Mean	95% Confidence Interval of the Difference		t	df	Sig. (2-tailed)
					Lower	Upper			
Pair 1	AsBuilt - FlashingBeacon	.55106	.65575	.10929	.32918	.77293	5.042	35	.000

From this analysis, it can be further confirmed that there is a significant difference in crossing speeds between the As-Built and Flashing Beacons environment. Table 32 below shows that the estimated effect size is .840, indicating a large effect on average crossing speed.

Table 32– Independent means paired t-test for crossing speeds between As Built and Flashing Beacons effect sizes

Paired Samples Effect Sizes

			Standardizer[a]	Point Estimate	95% Confidence Interval	
					Lower	Upper
Pair 1	AsBuilt - FlashingBeacon	Cohen's d	.65575	.840	.455	1.217
		Hedges' correction	.66288	.831	.450	1.204

a. The denominator used in estimating the effect sizes.
Cohen's d uses the sample standard deviation of the mean difference.
Hedges' correction uses the sample standard deviation of the mean difference, plus a correction factor.

As Built vs Phone App

The descriptive statistics and results of the paired t-test are shown in Table 33 below.

Table 33– Independent means paired t-test for crossing speeds between As Built and Phone App

Paired Samples Statistics

		Mean	N	Std. Deviation	Std. Error Mean
Pair 1	AsBuilt	3.6357	35	.70803	.11968
	PhoneApp	2.8776	35	.49740	.08408

Paired Samples Test

		Paired Differences					t	df	Sig. (2-tailed)
		Mean	Std. Deviation	Std. Error Mean	95% Confidence Interval of the Difference				
					Lower	Upper			
Pair 1	AsBuilt - PhoneApp	.75818	.70051	.11841	.51755	.99882	6.403	34	.000

From this analysis, it can be further confirmed that there is a significant difference in accepted gap size between the As-Built and Phone App environment. Table 34 below shows that the estimated effect size is 1.082, indicating a large effect on average crossing speed.

Table 34– Independent means paired t-test for crossing speed between As Built and Phone App

Paired Samples Effect Sizes

			Standardizer[a]	Point Estimate	95% Confidence Interval Lower	95% Confidence Interval Upper
Pair 1	AsBuilt - PhoneApp	Cohen's d	.70051	1.082	.658	1.496
		Hedges' correction	.70836	1.070	.651	1.480

a. The denominator used in estimating the effect sizes.
Cohen's d uses the sample standard deviation of the mean difference.
Hedges' correction uses the sample standard deviation of the mean difference, plus a correction factor.

This effect size is similar to what we see in the Flashing Beacons environment, though it is a little larger. Variance in the effect size could be attributed subjects either feeling safer with the phone app technology, rather than the flashing beacons, or, adversely, subjects may be more cautious when crossing the road when using the phone app and cross slower. Referencing the survey data in Table 15 from Chapter 5.3.5, 56% of subjects stated that they felt safe crossing the road using the mobile phone app, whereas 90% of subjects felt safe when crossing the street using the flashing beacons, thus, it may be inferred that the latter interpretation that subjects may be more cautious when crossing the road with the phone app due to the unfamiliarity of the technology is the more likely reasoning for this larger effect size. Comparatively, 26.5% of participants stated that they felt safe crossing the road in the As-Built environment, thus, the alternative technologies not only increased pedestrians' perception of safety when crossing, but decreased their crossing speeds, indicating safer crossing behavior.

6.4 VR Safety Analysis Discussion

The second goal of this dissertation was to understand pedestrian preferences (both stated and observed) and behavior in regards to alternative infrastructure technology and design at midblock crosswalks. Chapter 6 provided an analysis between alternative safety measures in an IVE, proving the efficacy of VR technology in studying the safety implications of such designs without the time, cost, and safety risks of implementing these alternatives in the real world.

Correlations

Bivariate correlations were conducted to determine the effect coefficients of each of the dependent variables to best understand how they were affecting pedestrian behavior as well as to what extent they were impacting it.

Accepted gap number, accepted gap size, and crossing speed all had negative correlations with the environment variables, indicating that as the environment switches between the As Built to the Flashing Beacons and Phone App, gaps are accepted sooner, accepted gap size decreased, and crossing speed decreased. The negative accepted gap number correlation was a strong correlation as most subjects used the alternative technologies on either the first or second gap of the study for each environment. Gap size decreased between the As-Built and the alternative scenarios because the accepted gap size of the As-Built scenario was weighted towards larger gap sizes, whereas the accepted gap size of the alternatives was limited to whatever gap showed up first or second. Crossing speed also had a moderately negative correlation because pedestrians didn’t have to cross in between vehicles that were not yielding for the pedestrian in the alternative environments, but instead waited for or expected them to yield the right of way and crossed slower.

There was a strong positive correlation between the environments and the reaction to the last vehicle which is categorized as (1) crossed during gap and (2) waited for approaching vehicle to stop. This variable is expected to be positive because the As Built environment vehicles never yielded for the pedestrian before they were crossing, but only when they were in the lane of traffic, in which case the reaction to the last vehicle would still be coded as “1”. With the alternative technologies, most subjects waited for traffic to yield before crossing, though not all did.

With respect to the Flashing Beacons environment, 9 of the 42 – 21.4% – subjects who did use the flashing beacons crossed before vehicles yielded the right of way. In the Phone App environment, 10 of the 43 – 23.3% – subjects who did use the phone app crossed before vehicles yielded the right of way. Since both of these percentages are similar, it could be inferred that the level of trust for each technology is similar. Further analysis with eye tracking is suggested with respect to the implications of this behavior to determine whether or not this is unsafe behavior. Analyzing whether pedestrians are attentive during crossing and actively looking at approaching vehicles may suggest safer crossing behavior rather than pedestrians not watching approaching traffic and blindly trusting the alternative technologies. The argument could be made that in a fully connected and autonomous environment where approaching vehicles would yield the right of way, as did all vehicles in this study, that this would be efficient behavior, but this simply not the reality of modern-day crossing scenarios. Another argument could be made to further test the mobile phone application with feedback provided to the pedestrian when approaching vehicles are yielding the right of way, rather than just confirming that the pedestrian’s intent to cross is being broadcasted. This approach would essentially act like a handshake where both users express their intent to cross and yield, offering the safest approach, and could offer further insight into pedestrian trust in the technology with this added layer of information and possibly answer the question: would pedestrians cross before receiving this confirmation that it is safe to cross at the same rate?

Furthermore, in order to determine whether the dynamic constants in the experiment, the order of which each environment was experienced and the randomized vehicle models presented to the subjects, had a significant impact on subject behavior, these constants were treated as variables in the same Spearman correlation and were not found to have a significant impact on subject behavior nor was there any significant bias in the randomization of the order of vehicle model in any of the environments. This analysis demonstrated the capability IVEs provide for controlling environmental factors that may otherwise have an influence on real-world data.

Accepted Gaps

Alternative safety treatments and technologies were shown to have large impacts on the crossing behavior of pedestrians at uncontrolled crossings. With respect to gap size, the use of a repeated measures ANOVA test has proven that there are strong statistically significant differences between gap acceptance with and without alternative technologies. The explanation for these differences was found to be rather simple: pedestrians accepted the first or second gap with alternative technologies because they could use it immediately, whereas in the As-Built scenario, they didn't have any means of communicating with approaching traffic and had to choose a gap they felt was safe without that communication, thus leading to more rejected gaps.

There was no significant difference found between gap size between the Flashing Beacons and the Phone App because both alternatives operated the same way; however, subject perceptions of these technologies did differ in the post-experiment survey. 56% of subjects felt safe crossing the road using the mobile phone application whereas 90% of subjects felt safe crossing the road using the flashing beacons. There are multiple reasons for why the perception of these two technologies may be different, even though they operated in nearly the exact same way. For one, Flashing Beacons have been around for quite a while and most people are very familiar with using them. Similarly, CV technology is rather new and there may be a lack of trust in this technology. Fundamentally, the two alternatives acted in the same way, there was no feedback sent to the pedestrian that indicated it was safe to cross with either technology, but only a visual response that their intent to cross was being communicated: for the flashing beacons, the flashing is visible, for the phone app, a message is sent indicating that their request to cross is being broadcasted. The difference between these two is that for the Flashing Beacons, the pedestrian's intent to cross is globally visual, anyone near it could see it; however, with the Phone App, only the pedestrian can see the message on their phone that their request is being broadcasted. While the driver is still receiving this message, there may be a level of mistrust in message being sent out because it is a personal message and not a global one, even if the message is being sent to all drivers globally within range.

Crossing Speed

Crossing speed is used to understand whether pedestrians are crossing the road safely or feel the need to dash across the road. A repeated measures ANOVA test was used again and showed strong statistically significant differences in crossing speeds in the As-Built environment when compared to the environments with alternative technologies. Pedestrians crossed the street at higher speeds in the As-Built environment than either alternative technology, however there was no significant difference in crossing speeds between the Flashing Beacons and Phone App. Furthermore, when comparing speeds, it was found that the impact of alternative technologies on crossings speeds had a large effect in reducing the mean crossing speed at the crossing while also reducing the variance of crossing speeds, indicating a safer crossing environment. In comparing the post-experiment survey responses, 26.5% of respondents felt safe in the As-Built environment, 90% with the Flashing Beacon, and 56% with the Phone App. These responses further confirm that uncontrolled crossing safety could be analyzed in IVEs as well as for determining the impacts the alternative technologies have on crossing safety.

Chapter 7: Conclusions and Future Work

7.1 Conclusions and Contributions

This dissertation investigated the use of VR technology for studying pedestrian behavior and safety. The goal of this dissertation was twofold:

I. Pedestrian VR Simulator Validation: Prove the feasibility of utilizing virtual reality technology as a tool for conducting real-world experimentation of pedestrian behavior.

II. Safety Analysis of Alternative Pedestrian Crossing Technologies: Understand pedestrian behavior and preferences (both stated and observed) in regards to alternative safety technology at midblock crosswalks.

7.1.1 Goal I: Pedestrian VR Simulator Validation

Chapter 5 provided a validation analysis between real-world and virtual behavior in an IVE that was modelled on a one-to-one scale of a real-world, high-risk environment, proving the feasibility of utilizing VR technology as a tool for conducting real-world experimentation of pedestrian behavior. Two variables were considered as the main indicators of pedestrian behavior and safety: accepted gap size and average crossing speed.

Accepted Gaps

Accepted gap size is indicative of pedestrians' perception of safety at a crosswalk and is arguably the standard for determining the safety of an uncontrolled crossing aside from crash analyses. It represents the threshold of risk pedestrians are will to accept before rejecting a gap. To validate an IVE, it is paramount that this risk be similar to the real-world environment it is modelled after so that further analysis of the crossing location in VR could be used for real-world practice.

Comparing gap acceptance via chi-square analysis of distributions, VR and real-world environments are similar and the use of IVEs for studying pedestrian safety at uncontrolled crossings is a valid approach. 94% of subjects felt they were immersed in the environment, 86% felt that their experience in the IVE was consistent with their real-world experiences, and 92% felt that their sense of movement and walking speed was realistic in the IVE. With respect to risk, 58% reported that their sense of risk was realistic, though, 30% reported it was somewhat realistic and only 12% reported that it was unrealistic. Comparing these results with the 54% of subjects who felt that the traffic was realistic in the IVE, it can be inferred that the realism of the traffic was most likely the cause for any changes in perception of risk, but that, generally, the IVE was well received and considered realistic, further validating the use of IVE for studying pedestrian safety at uncontrolled crossings.

Crossing Speed

Average crossing speeds are indicative of the safety of a pedestrian's crossing. Uncontrolled crossings experience variances in crossing speeds based off of pedestrians' behavior and perception of risk – pedestrians may walk across a road slowly with caution or may dart across the road to reduce their exposure to oncoming traffic, the latter approach being considered a sign of unsafe crossing behavior in research. Analyses showed that both average crossing speed and crossing speed variance did not differ between the VR simulator and real-world pedestrian behaviors, validating that pedestrians crossed with the same behavior and risk in the IVE as they did in the real-world. Comparing these results with the survey responses in Chapter 5.3.5, 92% of subjects felt that their sense of movement and their sense of walking speed inside the IVE was realistic, further validating the efficacy of the use of IVEs.

7.1.2 Goal II: Safety Analysis of Alternative Pedestrian Crossing Technologies

Chapter 6 provided an analysis between alternative safety measures in an IVE, proving the efficacy of VR technology in studying the safety implications of such designs without the time, cost, and safety risks of implementing these alternatives in the real world.

Correlations

Bivariate correlations were conducted to determine the effect coefficients of each of the dependent variables to best understand how they were affecting pedestrian behavior as well as to what extent they were impacting it. Accepted gap number, accepted gap size, and crossing speed all indicated that as the environment switched between the As Built to the Flashing Beacons and Phone App, gaps were accepted sooner, accepted gap sizes decreased, and crossing speeds decreased. With respect to the Flashing Beacons environment, 9 of the 42 – 21.4% – subjects who did use the flashing beacons crossed before vehicles yielded the right of way. In the Phone App environment, 10 of the 43 – 23.3% – subjects who did use the phone app crossed before vehicles yielded the right of way, suggesting that the level of trust for each technology was similar. Furthermore, the dynamic constants in the experiment – the order of which each environment was experienced and the randomized vehicle models presented to the subjects – did not have a significant impact on subject behavior. This analysis demonstrated the capability IVEs provide for controlling environmental factors that may otherwise have an influence on real-world data.

Accepted Gaps

Alternative safety treatments and technologies were shown to have large impacts on the crossing behavior of pedestrians at uncontrolled crossings. With respect to gap size, the use of a repeated measures ANOVA test has proven that there are strong statistically significant differences between gap acceptance with and without alternative technologies.

There was no significant difference found between gap size between the Flashing Beacons and the Phone App because both alternatives operated the same way; however, subject perceptions of these technologies did differ in the post-experiment survey. 56% of subjects felt safe crossing the road using the mobile phone application whereas 90% of subjects felt safe crossing the road using the flashing beacons.

Crossing Speed

Crossing speed were used to understand whether pedestrians were crossing the road safely or felt the need to dash across the road. A repeated measures ANOVA test showed strong statistically significant differences in crossing speeds in the As-Built environment when compared to the environments with alternative technologies. Pedestrians crossed the street at higher speeds in the As-Built environment than either alternative technology, however there was no significant difference in crossing speeds between the Flashing Beacons and Phone App. Furthermore, when comparing speeds, it was found that the impact of alternative technologies on crossings speeds had a large effect in reducing the mean crossing speed at the crossing while also reducing the variance of crossing speeds, indicating a safer crossing environment. In comparing the post-experiment survey responses, 26.5% of respondents felt safe in the As-Built environment, 90% with the Flashing Beacon, and 56% with the Phone App. These responses further confirm that uncontrolled crossing safety could be analyzed in IVEs as well as for determining the impacts the alternative technologies have on crossing safety.

7.1.3 Research Contributions

This dissertation contributes to the body of knowledge in pedestrian simulation, behavior, and connected vehicle technology in the following ways:

i. *Validation of VR Simulator*

   This dissertation presents a validation analysis between real-world and virtual behavior in an IVE that is modelled on a one-to-one scale after the real-world environment that proved the feasibility of utilizing VR technology as a tool for conducting real-world experimentation of pedestrian behavior. Previous literature shows that few simulation studies validate their IVEs or even model them off of real-world locations to replicate and understand on-site operations and those that do rely mostly on stated response surveys.

ii. *Alternative Safety Technology*

   This dissertation presents an analysis of alternative safety measures in an IVE compared against the as-built design. This analysis proved the efficacy of VR technology in studying the safety implications of such designs without the time, cost, and safety risks of implementing these alternatives in the real world.

iii. *VR Simulation Methodology*

This dissertation discussed in detail the development of a VR simulation experiment methodology for validating and testing pedestrian safety. Previous literature shows that there is a lack of standard practices when testing pedestrians within VR, hence, there is no cross comparison between VR simulator results. The presented methodology in this research could be used by researchers as a guideline for standard practices for developing discrete simulators that could be cross-analyzed.

iv. *VR Simulator Development*

This dissertation discussed in detail the considerations, elements, system design, and development of a comprehensive, multimodal data-collecting, VR simulator that provides never before collected data sources with commercially available technologies. The data collected by the simulator developed in this dissertation offers new insight into the behaviors of VRUs to fully understand and design for behavior and preference. Furthermore, the presented simulator is entirely replicable and may be used for many purposes, not limited to:

- Safety and/or human factors research
- Public demonstration and outreach by local or state governments
- Education for children and/or citizens
- Operations and/or design simulation for contractors

v. *Vulnerable Road User Simulation and CV/AV Technology*

This dissertation expands the traditional methods of simulation research to include VRUs in a fully immersible, interactable, and realistic simulation that offers full range of movement. Previous simulation research is highly driver-centric, focusing more on only driver behavior and less on driver-VRU interaction, primarily because of the risks and need for unrealistic control for safety inherent in real-world pedestrian studies. Furthermore, this dissertation also provides a novel approach to the development and implementation of connected and automated vehicle technology applications from the perspective of a VRU. With the development and deployment of CV/AV technology there is greater emphasis placed on understanding VRU behavior and safety since VRUs may be the only unconnected or human decision-making users on the roadway, thus, this research addresses the space in which researching the safety implications of new technologies without the risk to VRUs is possible.

7.2 Future Work

During the development and use of the VR simulator in this dissertation, several topics were identified as areas of future research.

i. *Multiple subjects in VR*

This research only included one user within the simulation to understand their behavior in a very controlled setting, though, in real-life, multiple users are on the roadway. Expanding the simulators capabilities to multiple users within VR would offer a completely new and safe way to understand operations and safety as never before. The incorporation of a driving simulator into the environment alongside both the pedestrian and cyclist simulators would provide a platform to test and understand new roadway designs and technologies with all of the perceived risks inherent in the real-world environment.

ii. Multiplayer Online Roleplaying Simulation

The simulator developed within this research was done using entirely commercially available technology and is entirely replicable by anyone who wishes to do so. A research area not mentioned in any literature is the development of an entirely virtual environment that is accessible by multiple users remotely, and synchronously, similar to how an online video game is accessed. This first step to this approach would probably require a partnership with another research facility, university, state DOT, or other funding source to develop identical simulators running not on the same computer, but on the same server, so that multiple users may access the IVE and interact with one another. This could be used as a crowd-sourced approach to collecting data on user interactions, simply replacing a simulated user in the environment with a real one when they would enter it. Furthermore, this would serve as a great demonstration for how new technologies and designs can be remotely experienced by many stakeholders, contractors, etc.

iii. Pedestrian feedback on CV mobile crossing app

Within the mobile phone crossing application simulation environment in this study, participants who used the phone app to assist in crossing received a message on the cell phone app that their request to cross is being broadcasted. As previously mentioned, this message confirms that the message is being sent out, but it does not inform the user of approaching vehicle intent. Based on the feedback of subjects in the experiment, it would be interesting to test operations should the cell phone provide a message back to the user when it is safe for them to cross. This approach would be beneficial both for testing pedestrian behavior and preference with connected technology but also for understanding pedestrian trust in autonomous technology.

7.3 Previous Publications and Conference Presentations

2017 VASITE/ITSVA Guest Speaker – User Recognition at Mid-Block Crossings via Connected Vehicle Technology

Presentation of experimental design of research being conducted at Turner Fairbank Highway Research Center in developing a cellular application to warn drivers of pedestrians' intent to cross midblock crosswalks.

2018 TRB FHWA Exhibition – User Recognition at Mid-Block Crossings via Connected Vehicle Technology

Demonstrations at 2018 TRB of the cellular midblock crossing application.

2018 University of Virginia, Civil Engineering - School of Engineering and Applied Science, MS (Master of Science) – User Recognition at Midblock Crossings via Connected Vehicle Technology: An Evaluation of Driver Awareness via Eye Tracking and Stated Preference Data

Master's Thesis regarding the cellular midblock crossing application detailing the experimentation and results of daytime driver response and feedback testing of the application.

2019 TRB DDTEFP Innovative Doctoral Research Showcase – User Recognition at Midblock Crossings via Connected Vehicle Technology: An Evaluation of Driver Awareness via Eye Tracking and Stated Preference Data

Selectee of doctoral Eisenhower Fellowship recipients to present and showcase research at the 2019 TRB conference. Presentation discussed the findings from the master's thesis including the night time testing that was also conducted in the summer of 2018.

2019 TRB Presentation – Advance In-Vehicle Warning Messages on Drivers Approaching Mid-Block Crosswalks

Podium presentation at the 2019 TRB conference detailing the same findings as discussed in the *2019 TRB DDTEFP Innovative Doctoral Research Showcase.*

2019 TRB Presentation - Development of virtual reality simulators to assess perceived safety of vulnerable road users. *Federal Highway Administration's Dwight D. Eisenhower Innovative Doctoral Research Showcase

2019 TRB Presentation - Should DSRC and C-V2X Coexist? Debate.

2020 TRB Presentation - The use of virtual reality simulators in bicycle and pedestrian human subject testing: A synthesis.

2021 TRB Presentation - Development of virtual reality simulators to assess perceived safety of vulnerable road users.

7.4 Expected Papers

Papers in Review

Evaluation of driver performance with a prototype cyber physical mid-block crossing advanced warning system

Submitted to: Journal of Safety Research

Date: September 2020

Status: This paper was reviewed and some minor revisions were requested for publication. Currently, the paper has be returned with revisions and is under further review for publication.

This paper is a more comprehensive statistical approach in analyzing the performance metrics from my master's thesis. Statistical methods involved include covariance analysis and binomial logit modelling to determine what factors had the strongest statistical significance in subject decision making. Analysis proved that the warning application was the most statistically significant factor in whether the drivers stopped for the pedestrian at the midblock crossing.

Papers to be Written

The Use of Virtual Reality Simulators in Bicycle and Pedestrian Human Subject Testing: A Synthesis

Target Journal: Frontiers in Future Transportation - *In Prep*

This paper was written to serve as a comprehensive literature review pertaining to the use of virtual reality experimentation with pedestrians and cyclists over the last three decades, describing the inception of the technology's use in vulnerable road user related research through the current state of the art research. The paper discusses the goals, methods, technologies, and performance measures used in these studies so the reader has a better understanding of the trends in use of virtual reality and how it may be used in the near future as well as an understanding of the limitations and research gaps in these experiments.

Validation of Virtual Reality as a Tool for Simulating Pedestrian Crossing Behavior at Midblock Crosswalks

Target Journal: Transportation Research: Part F: Traffic Psychology and Behavior

This aim of this paper relates to Goal I of this proposal to demonstrate the similarities between observed crossing behaviors of pedestrians at midblock crossings in both real world and virtual environments. This paper will serve as a proof of concept for researchers interested in the rapidly growing field of virtual reality testing in transportation studies.

Understanding Pedestrian Behavior and Interaction with Alternative Technological Assistance at Midblock Crosswalks in Virtual Reality

Target Journal: Transportation Research: Part F: Traffic Psychology and Behavior or TRB TRR.

The aim of this paper relates to Goal II of this proposal to demonstrate the similarities and differences between pedestrian crossing behavior at midblock crossings with marked crosswalks, marked crosswalks with rapid flashing beacons, and marked crosswalks with the cellular midblock crossing application as tested from the driver perspective in the *Cellular Midblock Crossing Warning Application: The Effects of Advanced Warning Messages on Driver Behavior and Reaction* paper submitted for review. This paper will expand upon the aforementioned *Validation of Virtual Reality as a Tool for Simulating Pedestrian Crossing Behavior at Midblock Crosswalks* paper by demonstrating the use of virtual reality to study new design and technology concepts in pedestrian crossing behavior at midblock crosswalks without the need of constructing a test bed nor worry of designing a risk-free real-world test.

Understanding Pedestrian Preferences, Choice Factors, and Physiological Feedback in Virtual Reality

Target Journal: Transportation Research: Part F: Traffic Psychology and Behavior or TRB TRR.

The aim of this paper is to analyze the physiological data collected within this paper to determine the differences in pedestrian stated preference responses and physiological feedback. This paper would offer new insight into what scenarios trigger certain physiological responses – in this instance eye tracking behavior and hear rate – and how these responses may influence the choices pedestrians make when crossing the street in the As-Built and technology environments.

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Appendix A: Pre-Experiment Questionnaire

See attached

Appendix B: Post-Experiment Questionnaire

See attached

Appendix C: Testing Script

Welcome
Welcome to the Omni-Reality and Cognition Laboratory and thank you for this participation in this study and for taking the time to complete the pre-experiment questionnaire. Today, you will be entering a virtual environment modeled after the Water Street corridor parallel to the downtown mall in Charlottesville, VA as a pedestrian. Your task as a pedestrian is to cross the street within the virtual environment.

During this experiment, you will be wearing a virtual reality headset equipped with eye tracking technology, and handheld controllers. Before we begin the experiment, you will be placed within the virtual environment so that you can familiarize yourself with the controls and we can calibrate your movements. Video recording of your actions will be recorded in the virtual environment as well as in the testing room.

Should you have any questions or concerns during the test please feel free to ask me at any time. Should you experience any motion sickness and wish to exit the virtual environment, please let me know at any moment. Once the test is complete, I will ask you to remove the headset and you will be given a questionnaire. Once that is complete, we will advance to the next part of the experiment, afterwards, you will fill out one more questionnaire and be paid for your time here. All data from this test will be made public, however, none of the data collected will in any way, shape, or form, identify you as having been a test subject. Do you have any questions for me before we begin the calibration and testing?
Place smartwatch on participants' wrist and start the recording app

Familiarization
Start by facing in the direction of the arrow on the ground. Clip the battery pack to yourself, and then put on the HTC VIVE headset and make any appropriate adjustments so that it fits snug on your head. There is a strap on the top of the headset that adjusts the height that the headset sits on your head and a knob on the back of the headset that adjusts the width of the headset (Researcher can use spare headset as a demonstration here).

Pick up the controllers at your feet and face in the direction of the arrow on the ground. On the bottom of each virtual controller you will see a hand logo indicating which hand each controller represents, please be sure that the hand with the thumb on the right side of the hand is in your left hand and that the controller with the thumb on the left side of the hand is in your right hand. You will be placed within the testing environment shortly so that you many familiarize yourself with the controls and experience of virtual reality.

Eye Tracking
Next, I will guide you through the eye tracking process. Look at the controller in your right hand, there is a button located at the bottom of the controller with a square on it. Press this button and a window will appear in front of you. On that window, in the bottom panel, there is a blue symbol of an eye; with your controller, point the laser pointer at this symbol and pull the trigger on the back of the controller. If there is no laser emitting from your right controller, pull the trigger on the back of the controller first.

Hit calibrate and follow the instructions

Once virtual environment has been loaded…

In order to move forwards, you walk forwards. You may change the direction you are walking by changing direction or turning around, but do note that the space that you may walk around within is limited and shown by a light blue grid that appears when you are near the edge of the space you can walk in. The virtual space is designed to be contained within the space of this room so that you do not walk into any objects or walls. Walk around for a bit to familiarize yourself with the environment.

Now that you have been familiarized with the environment, we may proceed to the next phase of the experiment. Should you wish you spend a bit more time within the familiarization environment, you are more than welcome to do so. When you feel that you are ready to move forward, let me know.

Experiment 1 - As Built

You will now be placed within the first of three environments. Your task is to cross the road when you are ready. Wait for the first car to drive by before you begin crossing.

Experiment 2 - RFB

You will now be placed within the second of three environments. There is a rapid flashing beacon with a functional button which you can use to cross the road if you wish. Your task is to cross the road when you are ready, wait for the first car to drive by before you begin crossing.

Experiment 3 - Phone Application

You will now be placed within the third of three environments. In this environment, you will have a cell phone in your right hand equipped with a cellular application that allows you to send a message to approaching vehicles of your intent to cross the road. The ability to send this warning message is restricted to the vicinity of the midblock crosswalk, you will know that you are able to send this message when the phone screen asks you if you’d like to cross the road. Your task is to cross the road in the manner you wish.

Debrief

You may now remove the headset and place it on the designated spot on the ground with your controllers. Experimentation within the virtual environment is now complete. During this test, we monitored your crossing behavior at the Water Street corridor and how that behavior changed with alternative technologies.

Post-Test

Now that you have finished the VR phase of the experiment, we ask that you fill out the survey on this computer. Once you have finished, let me know and I will pay you for your time. *Once complete, pay test subjects for their time.*

Appendix D: Participant Recruitment Email

The Omni-Reality and Cognition Lab (ORCL) at the University of Virginia invites you to participate in an exciting new experiment utilizing Virtual Reality technology to understand bicyclist and pedestrian behavior. Participation in this study involves entering a virtual environment as both a pedestrian and a bicyclist and navigating through multiple scenarios within the environment.

For a better understanding of what you will be doing during the experiment, you may watch these videos of the pedestrian experiment and bike experiment which show a lab view and a virtual reality view.

You must be 18 or older to participate in this study. Participants with colorblindness cannot participate in this study due to the nature of the virtual reality equipment. Furthermore, if you wear glasses, we highly recommend that you wear contacts if you wish to participate in the study, as those with glasses often have trouble wearing the headset comfortably. We apologize for any inconvenience.

University COVID-19 protocols are being strictly followed in this laboratory. All equipment will be sanitized prior to your use of it, and hand sanitizer and gloves will be available. Masks are required at all times in the lab. Please do not participate if you have any symptoms of COVID-19. We will give you a brief health screening 24 hours prior to your testing time, and again upon your arrival on grounds. All researchers present in the lab are participating in weekly COVID testing and daily health screenings. The lab is approximately 1000 square feet, with an occupancy of 4 people there is sufficient space for greater than 6 feet of distance between people.

Participation in this study will require one hour of time and participants will be compensated $15.

To sign up for a time slot, please follow this link. We are currently scheduling times into March.

If you are interested in getting more information about the study or have any concerns or questions, please contact us at orcl@virginia.edu. More information about our lab can be found here.

Donna Chen, Assistant Professor, Principal Investigator
Arsalan Heydarian, Assistant Professor
Austin Angulo, PhD Candidate
Erin Robartes, PhD Candidate
Xiang Guo, PhD Candidate

IRB-SBS Protocol #2148

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Department of Engineering Systems and Environment

Appendix E: Consent Form

Informed Consent Agreement

Please read this consent agreement carefully before you decide to participate in the study.

Purpose of the research study: The purpose of this research is to test the effectiveness of Virtual Reality (VR) as tool to replicate realistic environmental settings at a low cost while reducing risk to the user during experimentation. In this experiment, we aim to increase understanding of perceived safety and technological acceptance as it relates to bicyclists, pedestrians, and the road environment. This information can be used by planners and engineers to better design technology and infrastructure for bicyclists and pedestrians.

With VR, we can study human behaviors in settings/scenarios that (1) we have limited or no access to (e.g., design of a new intersection that has not been built yet) or (2) are considered high-risk environments for collecting real-life data (e.g., bicyclist safety or crash rates at an intersection and pedestrian crash rates at mid-block crossings). Additionally, these tools provide us the freedom to control and manipulate different variables of interest, which we might not have access to in real-life environments. By coupling VR tools with biometric sensors (e.g., eye trackers, biometric wearables, EEG devices) in addition to behavioral information, users' physiological information can also be collected and analyzed.

What you will do in the study: You will participate in one of two studies: the **Pedestrian** or **Bicyclist** study.

The goal of the **Pedestrian** Study is to place pedestrians in an environment in which they can naturally interact with vehicles. Specifically, this research aims to study how pedestrians behave in scenarios where they have to cross the street at a midblock crosswalk while interacting with multiple types of connected vehicle technologies and lack thereof. Furthermore, this research aims to alter this interaction by changing multiple factors in the experiment such as whether or not an approaching vehicle is autonomous with no driver. In this study, you will be asked to wear physiological sensing and virtual reality equipment. You will be placed in multiple virtual environments, each different from one another, and will be asked to perform actions such as "cross the road when you feel safe". You will be given a short questionnaire after each test in which you will respond to your thoughts and feelings regarding your experience.

The goal of the **Bicyclist** Study is to place bicyclists in an environment in which they can naturally interact with vehicles. The participant will be seated on a stationary bike and will be wearing a VR headset and physiological sensing. The instrumented bicycle will allow their actions to be replicated in the virtual environment (speeding up, slowing down, steering). Specifically, this research aims to study how bicyclists behave in scenarios where they are presented with different elements of roadway environments. These may include factors such as different types of bicycle infrastructure, lane widths, traffic volumes or surroundings. You will be given a short questionnaire after each test in which you will respond to your thoughts and feelings regarding your experience.

Time required: The study will require about 1 hour of your time.

Risks: The physical components of these tasks are not stressful, and include head and body turning, moving, and pointing. Light and sound intensities are well within normal ranges. The only foreseeable physical risks are slight eye strain, dizziness, and mild nausea. There are no known mental risks. You will be asked to remove the head mounted display if they experience any eye strain, dizziness, or nausea during the sessions. They will be given rest breaks in between the sessions. Upon request, you will also be allowed to stop and leave the experiment if you feel uncomfortable or cannot continue the experiment.

A loss of confidentiality would not put you at risk, and the researchers will use caution in handling the data.

Benefits: There are no direct benefits associated with the participation in this study. The proposed experiments are straightforward tests of performance and visual comfort using standard virtual environments displays and trackers.

Confidentiality: The information that you give in the study will be handled confidentially. Your information will be assigned a code number. The list connecting your email to this code will be kept in a locked file. When the study is completed and the data have been analyzed, this list will be deleted. Your name will not be used in any report. Once any data is deleted from a request, the changes will propagate correspondingly to the backup drives.

Voluntary participation: Your participation in the study is completely voluntary. Deciding not to participate will have no effect on your education at the University of Virginia.

Right to withdraw from the study: You have the right to withdraw from the study at any time without penalty.

How to withdraw from the study: If you want to withdraw from the study, please contact the ORCL lab at orcl@virginia.edu indicating that you would like to withdraw from the study. There is no penalty for withdrawing. You may request that your archived data to be destroyed upon withdrawing from the study.

Payment: You will receive a $15 gift card as payment for participating in the study.

If you have questions about the study, contact:

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To obtain more information about the study, ask questions about the research procedures, express concerns about your participation, or report illness, injury or other problems, please contact:

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Refer to IRB-SBS Protocol #2148

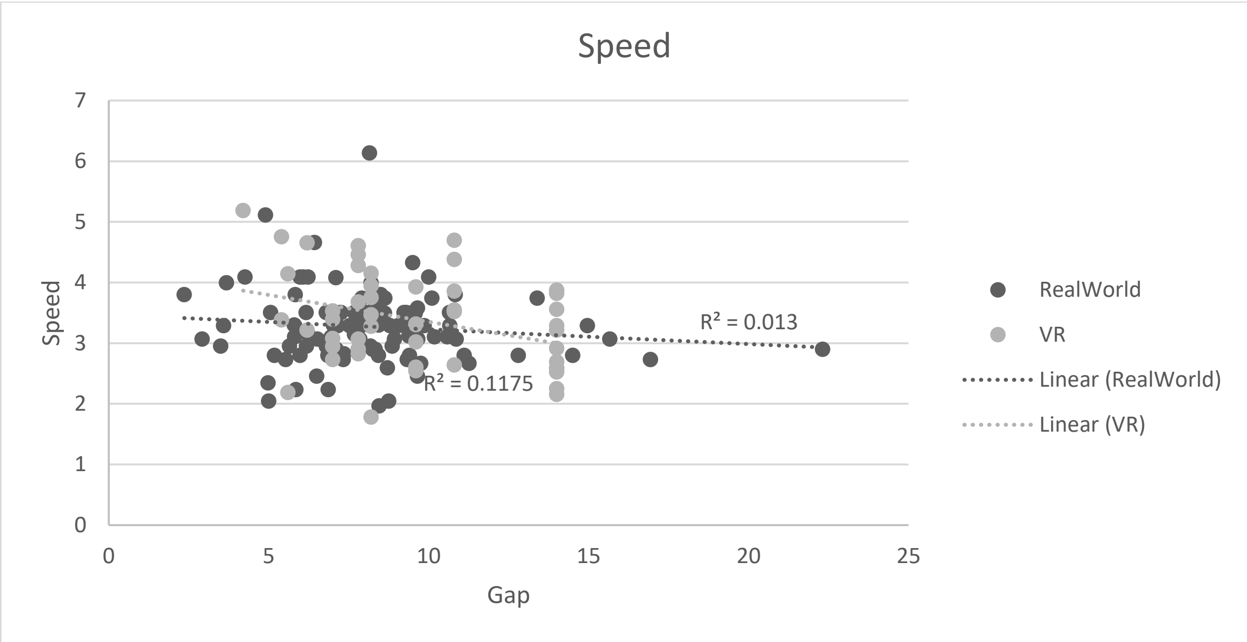
Agreement:
I agree to participate in the research study described above.

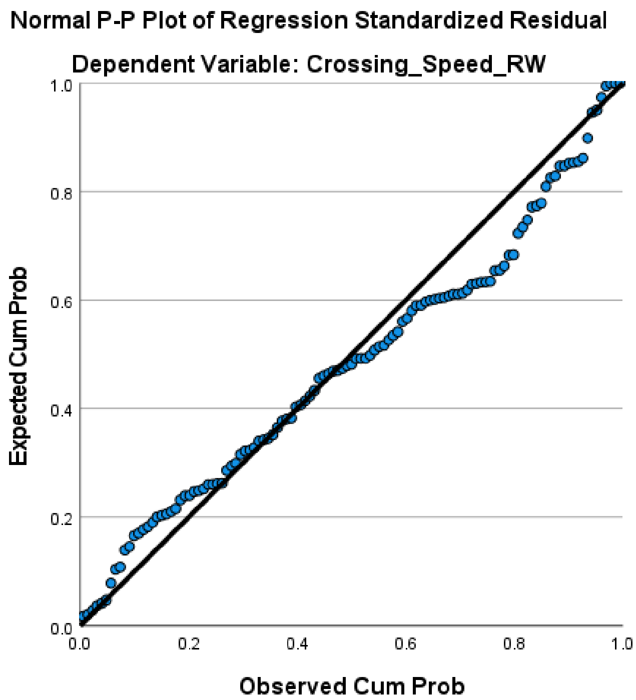
Signature: ____ Date: _____________

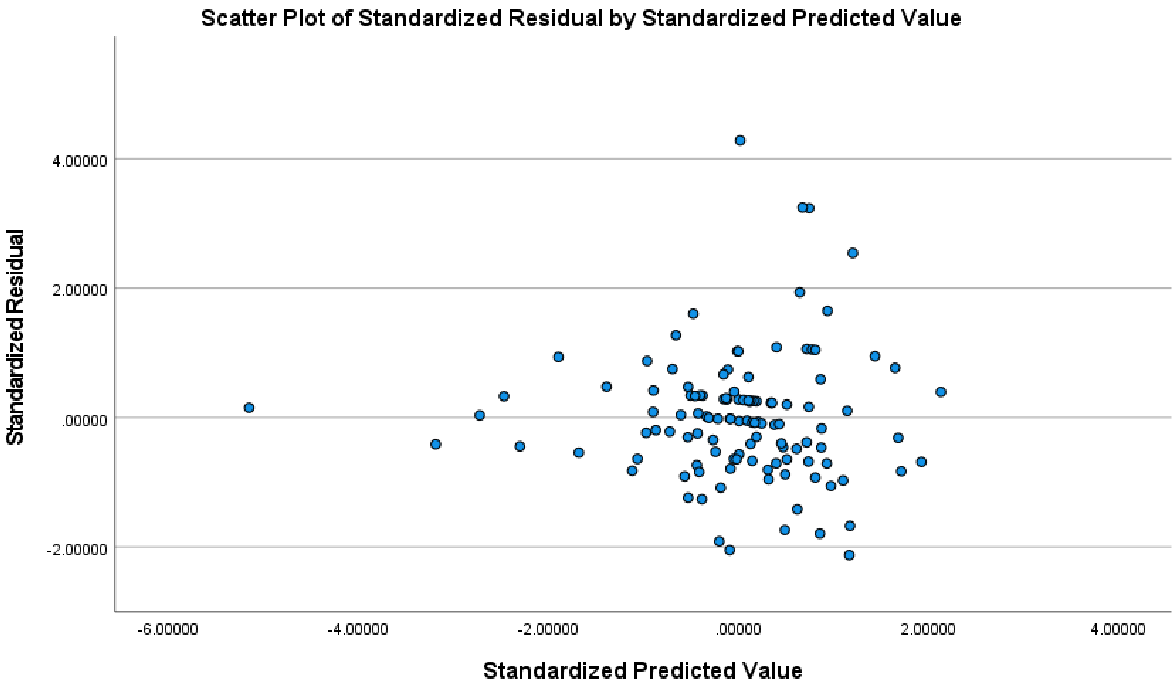
You will receive a copy of this form for your records.

Appendix F: Crossing Speed Model Fitting and Median Split

Speed






Scatter Plot of Standardized Residual by Standardized Predicted Value
Standardized Residual
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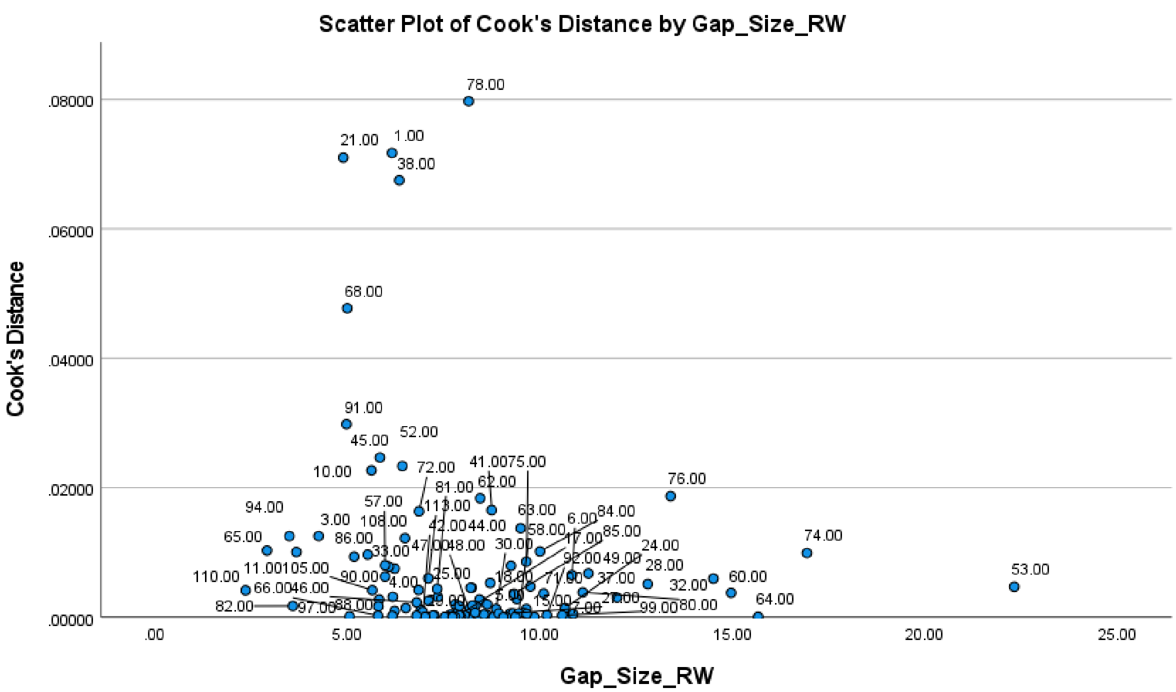
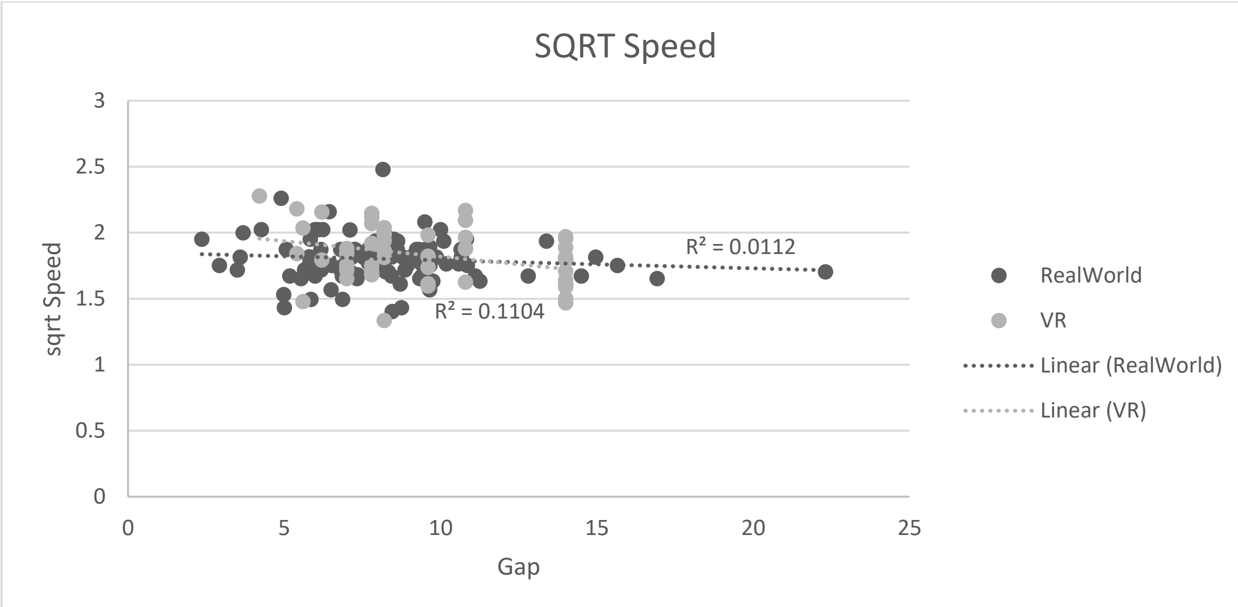
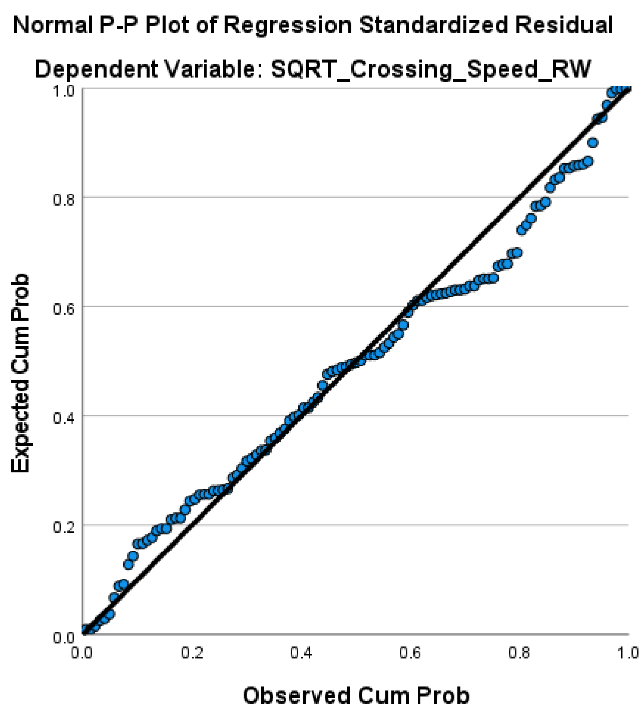
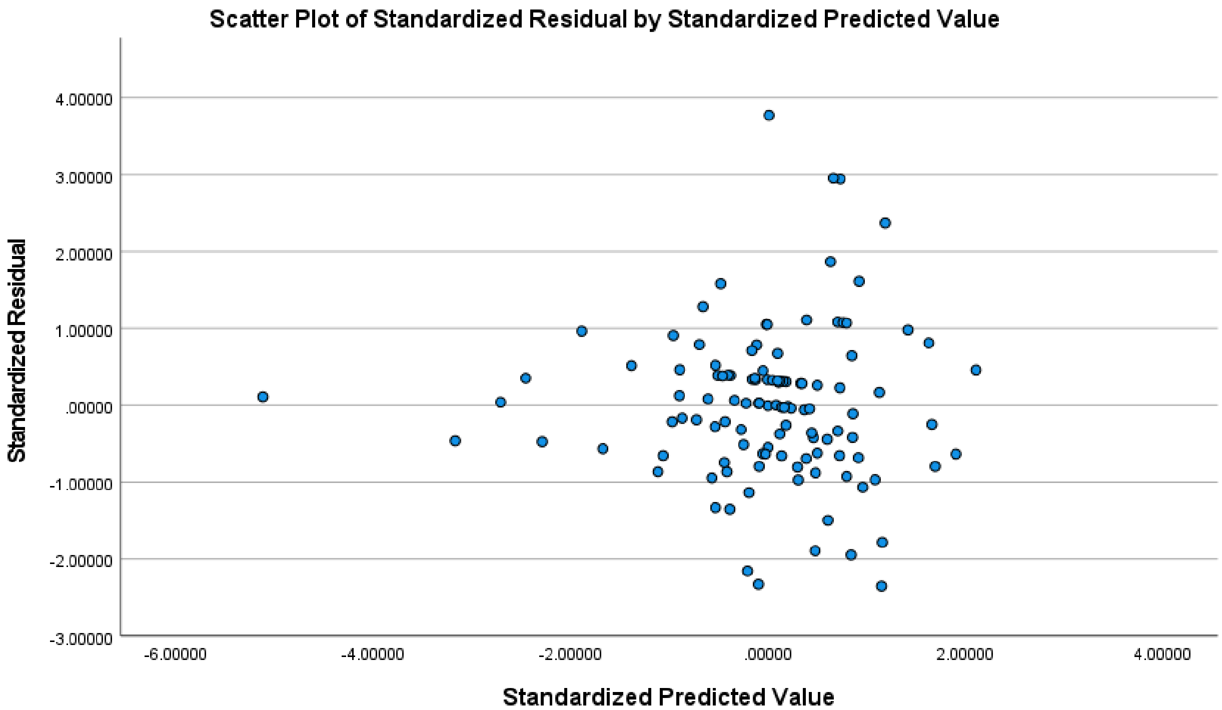
2.00000
.00000
-2.00000
-6.00000
-4.00000
-2.00000
.00000
2.00000
4.00000
Standardized Predicted Value

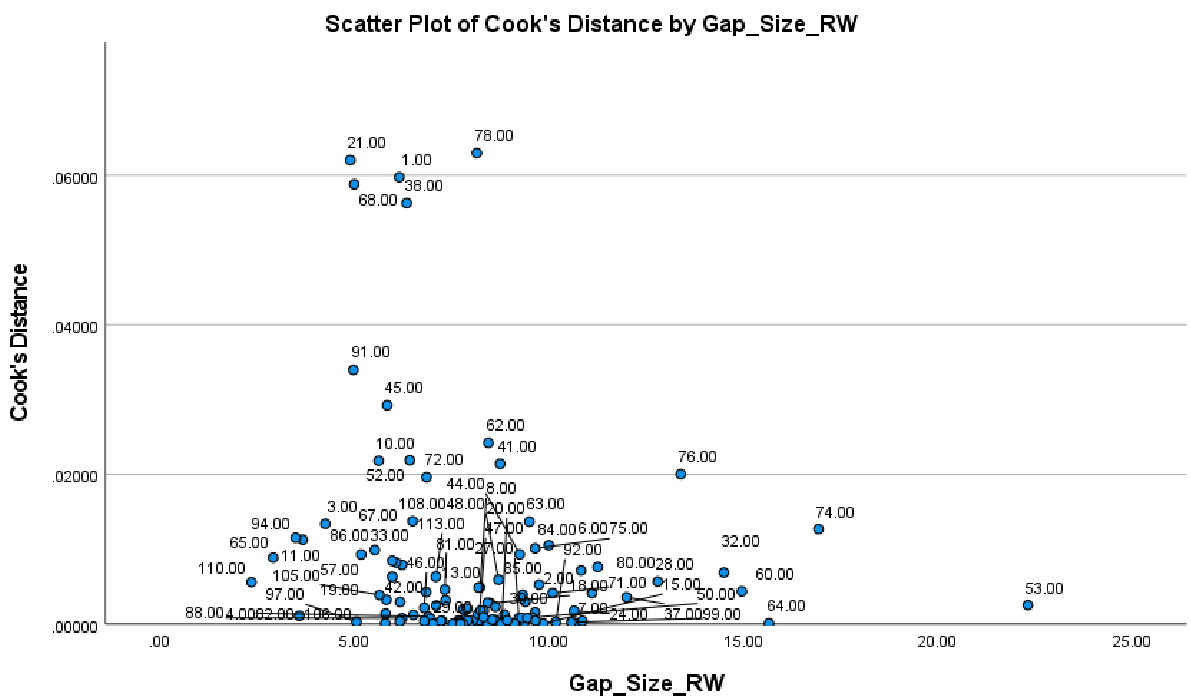

Scatter Plot of Cook's Distance by Gap_Size_RW
Cook's Distance
.08000
.06000
.04000
.02000
.00000
.00
5.00
10.00
15.00
20.00
25.00
Gap_Size_RW
78.00
21.00
1.00
38.00
68.00
91.00
52.00
45.00
76.00
74.00
53.00

Square Root Speed






Scatter Plot of Standardized Residual by Standardized Predicted Value
Standardized Residual
Standardized Predicted Value
4.00000
3.00000
2.00000
1.00000
.00000
-1.00000
-2.00000
-3.00000
-6.00000
-4.00000
-2.00000
.00000
2.00000
4.00000


Scatter Plot of Cook's Distance by Gap_Size_RW
Cook's Distance
Gap_Size_RW
.06000
.04000
.02000
.00000
.00
5.00
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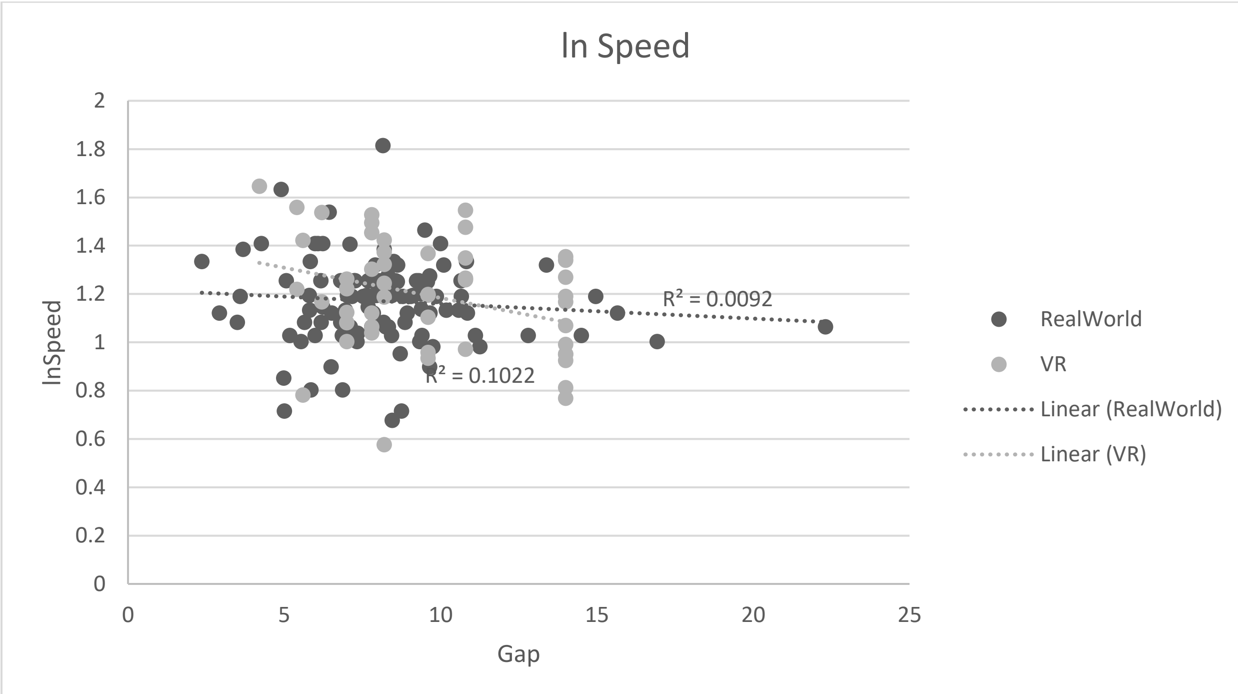
15.00
20.00
25.00
21.00
78.00
1.00
38.00
68.00
91.00
45.00
62.00
10.00
41.00
72.00
76.00
52.00
74.00
53.00
64.00

Natural Log Speed



Real-World Median Split

Group Statistics

	VAR00002	N	Mean	Std. Deviation	Std. Error Mean
VAR00001	.00	59	3.3836	.70803	.09218
	1.00	58	3.2579	.61122	.08026

Independent Samples Test

		Levene's Test for Equality of Variances		t-test for Equality of Means						
									95% Confidence Interval of the Difference	
		F	Sig.	t	df	Sig. (2-tailed)	Mean Difference	Std. Error Difference	Lower	Upper
VAR00001	Equal variances assumed	1.078	.301	1.028	115	.306	.12575	.12237	-.11665	.36815
	Equal variances not assumed			1.029	113.120	.306	.12575	.12222	-.11639	.36789

Appendix G: Accepted Gaps and Crossing Speeds for 49 Subject Dataset

Correlations

Spearman Correlations

		Environment	Order	Accepted Gap	Vehicle Model	Gap Size	Crossing Speed	Reaction to Last Vehicle
Environment	Correlation Coefficient	1	0.046	***-.679*****	0.139	***-.314*****	***-.350*****	***.737*****
	Sig. (2-tailed)		0.600	***0.000***	0.109	***0.000***	***0.000***	***0.000***
Order	Correlation Coefficient		1	-0.046	-0.012	-0.016	0.158	0.054
	Sig. (2-tailed)			0.600	0.889	0.855	0.069	0.537
Accepted Gap	Correlation Coefficient			1	-0.147	***.293*****	***.276*****	***-.640*****
	Sig. (2-tailed)				0.091	***0.001***	***0.001***	***0.000***
Vehicle Model	Correlation Coefficient				1	-0.137	0.059	0.126
	Sig. (2-tailed)					0.113	0.495	0.148
Gap Size	Correlation Coefficient					1	0.025	***-.483*****
	Sig. (2-tailed)						0.774	***0.000***
Crossing Speed	Correlation Coefficient						1	-0.151
	Sig. (2-tailed)							0.082
Reaction to Last Vehicle	Correlation Coefficient							1
	Sig. (2-tailed)							

*****. Correlation is significant at the 0.01 level (2-tailed).***

**. Correlation is significant at the 0.05 level (2-tailed).*

KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.734
Bartlett's Test of Sphericity	Approx. Chi-Square	247.414
	df	21
	Sig.	.000

Accepted Gaps

Descriptives

Gap_Accepted

	N	Mean	Std. Deviation	Std. Error	95% Confidence Interval for Mean Lower Bound	95% Confidence Interval for Mean Upper Bound	Minimum	Maximum
1.00	49	9.5469	2.98825	.42689	8.6886	10.4053	4.20	14.00
2.00	42	6.6476	3.08349	.47579	5.6867	7.6085	1.20	14.00
3.00	43	6.9721	3.18257	.48534	5.9926	7.9515	1.20	14.00
Total	134	7.8119	3.33428	.28804	7.2422	8.3817	1.20	14.00

Repeated Measures ANOVA

Descriptive Statistics

	Mean	Std. Deviation	N
AsBuilt	9.2000	2.97884	38
FlashingBeacons	7.0316	2.92853	38
PhoneApp	7.0263	3.29592	38

Mauchly's Test of Sphericity[a]

Measure: AcceptedGapSize

Within Subjects Effect	Mauchly's W	Approx. Chi-Square	df	Sig.	Epsilon[b] Greenhouse-Geisser	Epsilon[b] Huynh-Feldt	Epsilon[b] Lower-bound
Environments	.951	1.790	2	.409	.954	1.000	.500

Tests the null hypothesis that the error covariance matrix of the orthonormalized transformed dependent variables is proportional to an identity matrix.

a. Design: Intercept
Within Subjects Design: Environments

b. May be used to adjust the degrees of freedom for the averaged tests of significance. Corrected tests are displayed in the Tests of Within-Subjects Effects table.

Tests of Within-Subjects Effects

Measure: AcceptedGapSize

Source		Type III Sum of Squares	df	Mean Square	F	Sig.	Partial Eta Squared
Environments	Sphericity Assumed	119.408	2	59.704	6.945	.002	.158
	Greenhouse-Geisser	119.408	1.907	62.600	6.945	.002	.158
	Huynh-Feldt	119.408	2.000	59.704	6.945	.002	.158
	Lower-bound	119.408	1.000	119.408	6.945	.012	.158
Error(Environments)	Sphericity Assumed	636.192	74	8.597			
	Greenhouse-Geisser	636.192	70.577	9.014			
	Huynh-Feldt	636.192	74.000	8.597			
	Lower-bound	636.192	37.000	17.194			

Pairwise Comparisons

Measure: AcceptedGapSize

(I) Environments	(J) Environments	Mean Difference (I-J)	Std. Error	Sig.[b]	95% Confidence Interval for Difference[b] Lower Bound	Upper Bound
1	2	2.168*	.619	.004	.617	3.719
	3	2.174*	.653	.006	.537	3.810
2	1	-2.168*	.619	.004	-3.719	-.617
	3	.005	.741	1.000	-1.853	1.863
3	1	-2.174*	.653	.006	-3.810	-.537
	2	-.005	.741	1.000	-1.863	1.853

Based on estimated marginal means

*. The mean difference is significant at the .05 level.

b. Adjustment for multiple comparisons: Bonferroni.

Independent Means T-Test

As Built vs Flashing Beacon

Group Statistics

	Environment	N	Mean	Std. Deviation	Std. Error Mean
Gap_Accepted	1.00	49	9.5469	2.98825	.42689
	2.00	42	6.6476	3.08349	.47579

Independent Samples Test

		Levene's Test for Equality of Variances		t-test for Equality of Means						
									95% Confidence Interval of the Difference	
		F	Sig.	t	df	Sig. (2-tailed)	Mean Difference	Std. Error Difference	Lower	Upper
Gap_Accepted	Equal variances assumed	.070	.793	4.547	89	.000	2.89932	.63767	1.63228	4.16636
	Equal variances not assumed			4.536	85.985	.000	2.89932	.63923	1.62857	4.17007

Independent Samples Effect Sizes

		Standardizer[a]	Point Estimate	95% Confidence Interval Lower	Upper
Gap_Accepted	Cohen's d	3.03250	.956	.518	1.389
	Hedges' correction	3.05835	.948	.514	1.377
	Glass's delta	3.08349	.940	.476	1.395

a. The denominator used in estimating the effect sizes.
Cohen's d uses the pooled standard deviation.
Hedges' correction uses the pooled standard deviation, plus a correction factor.
Glass's delta uses the sample standard deviation of the control group.

As Built vs Phone App

Group Statistics

	Environment	N	Mean	Std. Deviation	Std. Error Mean
Gap_Accepted	1.00	49	9.5469	2.98825	.42689
	3.00	43	6.9721	3.18257	.48534

Independent Samples Test

		Levene's Test for Equality of Variances		t-test for Equality of Means						
									95% Confidence Interval of the Difference	
		F	Sig.	t	df	Sig. (2-tailed)	Mean Difference	Std. Error Difference	Lower	Upper
Gap_Accepted	Equal variances assumed	.074	.786	4.000	90	.000	2.57485	.64369	1.29604	3.85365
	Equal variances not assumed			3.984	86.713	.000	2.57485	.64637	1.29006	3.85963

Independent Samples Effect Sizes

		Standardizer[a]	Point Estimate	95% Confidence Interval	
				Lower	Upper
Gap_Accepted	Cohen's d	3.08046	.836	.406	1.261
	Hedges' correction	3.10643	.829	.403	1.251
	Glass's delta	3.18257	.809	.361	1.249

a. The denominator used in estimating the effect sizes.
Cohen's d uses the pooled standard deviation.
Hedges' correction uses the pooled standard deviation, plus a correction factor.
Glass's delta uses the sample standard deviation of the control group.

Paired Means T-Test

As Built vs Flashing beacon

Paired Samples Statistics

		Mean	N	Std. Deviation	Std. Error Mean
Pair 1	AsBuilt_AcceptedGap	9.3095	42	2.93081	.45223
	FlashingBeacon_AcceptedGap	6.6476	42	3.08349	.47579

Paired Samples Test

		Paired Differences							
					95% Confidence Interval of the Difference				
		Mean	Std. Deviation	Std. Error Mean	Lower	Upper	t	df	Sig. (2-tailed)
Pair 1	AsBuilt_AcceptedGap - FlashingBeacon_AcceptedGap	2.66190	4.09342	.63163	1.38631	3.93750	4.214	41	.000

Paired Samples Effect Sizes

			Standardizer[a]	Point Estimate	95% Confidence Interval	
					Lower	Upper
Pair 1	AsBuilt_AcceptedGap - FlashingBeacon_AcceptedGap	Cohen's d	4.09342	.650	.314	.980
		Hedges' correction	4.13134	.644	.311	.971

a. The denominator used in estimating the effect sizes.
Cohen's d uses the sample standard deviation of the mean difference.
Hedges' correction uses the sample standard deviation of the mean difference, plus a correction factor.

As Built vs Phone App

Paired Samples Statistics

		Mean	N	Std. Deviation	Std. Error Mean
Pair 1	AsBuilt_AcceptedGap	9.2651	43	2.94351	.44888
	PhoneApp_AcceptedGap	6.9721	43	3.18257	.48534

Paired Samples Test

		Paired Differences					t	df	Sig. (2-tailed)
					95% Confidence Interval of the Difference				
		Mean	Std. Deviation	Std. Error Mean	Lower	Upper			
Pair 1	AsBuilt_AcceptedGap - PhoneApp_AcceptedGap	2.29302	3.93019	.59935	1.08349	3.50256	3.826	42	.000

Paired Samples Effect Sizes

			Standardizer[a]	Point Estimate	95% Confidence Interval	
					Lower	Upper
Pair 1	AsBuilt_AcceptedGap - PhoneApp_AcceptedGap	Cohen's d	3.93019	.583	.257	.904
		Hedges' correction	3.96572	.578	.254	.896

a. The denominator used in estimating the effect sizes.
Cohen's d uses the sample standard deviation of the mean difference.
Hedges' correction uses the sample standard deviation of the mean difference, plus a correction factor.

Crossing Speeds

Only includes data from alternative environments in which subjects used the technology.

ANOVA

Descriptives

Crossing_Speed

	N	Mean	Std. Deviation	Std. Error	95% Confidence Interval for Mean Lower Bound	95% Confidence Interval for Mean Upper Bound	Minimum	Maximum
1.00	49	3.3919	.77188	.11027	3.1702	3.6136	1.78	5.19
2.00	43	2.9833	.48005	.07321	2.8355	3.1310	1.60	4.49
3.00	43	2.8447	.50386	.07684	2.6896	2.9997	2.03	4.46
Total	135	3.0874	.64924	.05588	2.9769	3.1979	1.60	5.19

ANOVA

Crossing_Speed

	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	7.543	2	3.771	10.172	.000
Within Groups	48.940	132	.371		
Total	56.483	134			

Since the number of comparisons is small (n is <50), the Bonferroni test is more powerful as well as more conservative to prevent Type I data (data from incorrectly appearing to be statistically significant). This test was used in previous literature as well.

Multiple Comparisons

Dependent Variable: Crossing_Speed

	(I) Environment	(J) Environment	Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval Lower Bound	95% Confidence Interval Upper Bound
Tukey HSD	1.00	2.00	.40862*	.12724	.005	.1070	.7102
		3.00	.54722*	.12724	.000	.2456	.8488
	2.00	1.00	-.40862*	.12724	.005	-.7102	-.1070
		3.00	.13860	.13132	.543	-.1727	.4499
	3.00	1.00	-.54722*	.12724	.000	-.8488	-.2456
		2.00	-.13860	.13132	.543	-.4499	.1727
Bonferroni	1.00	2.00	.40862*	.12724	.005	.1001	.7171
		3.00	.54722*	.12724	.000	.2387	.8558
	2.00	1.00	-.40862*	.12724	.005	-.7171	-.1001
		3.00	.13860	.13132	.879	-.1798	.4570
	3.00	1.00	-.54722*	.12724	.000	-.8558	-.2387
		2.00	-.13860	.13132	.879	-.4570	.1798

*. The mean difference is significant at the 0.05 level.

Independent Means T-Test

As Built vs Flashing Beacon

Group Statistics

	Environment	N	Mean	Std. Deviation	Std. Error Mean
Crossing_Speed	1.00	49	3.3919	.77188	.11027
	2.00	43	2.9833	.48005	.07321

Independent Samples Test

		Levene's Test for Equality of Variances		t-test for Equality of Means						
									95% Confidence Interval of the Difference	
		F	Sig.	t	df	Sig. (2-tailed)	Mean Difference	Std. Error Difference	Lower	Upper
Crossing_Speed	Equal variances assumed	11.322	.001	2.999	90	.004	.40862	.13627	.13789	.67935
	Equal variances not assumed			3.087	81.535	.003	.40862	.13236	.14529	.67194

Independent Samples Effect Sizes

		Standardizer[a]	Point Estimate	95% Confidence Interval Lower	95% Confidence Interval Upper
Crossing_Speed	Cohen's d	.65215	.627	.205	1.045
	Hedges' correction	.65765	.621	.204	1.036
	Glass's delta	.48005	.851	.399	1.295

a. The denominator used in estimating the effect sizes.
Cohen's d uses the pooled standard deviation.
Hedges' correction uses the pooled standard deviation, plus a correction factor.
Glass's delta uses the sample standard deviation of the control group.

As Built vs Phone App

Group Statistics

	Environment	N	Mean	Std. Deviation	Std. Error Mean
Crossing_Speed	1.00	49	3.3919	.77188	.11027
	3.00	43	2.8447	.50386	.07684

Independent Samples Test

		Levene's Test for Equality of Variances		t-test for Equality of Means						
									95% Confidence Interval of the Difference	
		F	Sig.	t	df	Sig. (2-tailed)	Mean Difference	Std. Error Difference	Lower	Upper
Crossing_Speed	Equal variances assumed	7.221	.009	3.965	90	.000	.54722	.13801	.27303	.82141
	Equal variances not assumed			4.072	83.446	.000	.54722	.13440	.27993	.81452

Independent Samples Effect Sizes

		Standardizer[a]	Point Estimate	95% Confidence Interval Lower	Upper
Crossing_Speed	Cohen's d	.66048	.829	.399	1.253
	Hedges' correction	.66605	.822	.396	1.243
	Glass's delta	.50386	1.086	.611	1.552

a. The denominator used in estimating the effect sizes.
Cohen's d uses the pooled standard deviation.
Hedges' correction uses the pooled standard deviation, plus a correction factor.
Glass's delta uses the sample standard deviation of the control group.

Paired Means T-Test

As Built vs Flashing Beacon

Paired Samples Statistics

		Mean	N	Std. Deviation	Std. Error Mean
Pair 1	AsBuilt_Speed	3.4619	43	.77763	.11859
	FlashingBeacon_Speed	2.9833	43	.48005	.07321

Paired Samples Test

		Paired Differences							
					95% Confidence Interval of the Difference				
		Mean	Std. Deviation	Std. Error Mean	Lower	Upper	t	df	Sig. (2-tailed)
Pair 1	AsBuilt_Speed - FlashingBeacon_Speed	.47860	.65736	.10025	.27630	.68091	4.774	42	.000

Paired Samples Effect Sizes

			Standardizer[a]	Point Estimate	95% Confidence Interval Lower	Upper
Pair 1	AsBuilt_Speed - FlashingBeacon_Speed	Cohen's d	.65736	.728	.388	1.061
		Hedges' correction	.66331	.722	.384	1.052

a. The denominator used in estimating the effect sizes.
Cohen's d uses the sample standard deviation of the mean difference.
Hedges' correction uses the sample standard deviation of the mean difference, plus a correction factor.

As Built vs Phone App

Paired Samples Statistics

		Mean	N	Std. Deviation	Std. Error Mean
Pair 1	AsBuilt_Speed	3.4519	43	.79060	.12057
	PhoneApp_Speed	2.8447	43	.50386	.07684

Paired Samples Test

		Paired Differences					t	df	Sig. (2-tailed)
					95% Confidence Interval of the Difference				
		Mean	Std. Deviation	Std. Error Mean	Lower	Upper			
Pair 1	AsBuilt_Speed - PhoneApp_Speed	.60721	.73694	.11238	.38041	.83401	5.403	42	.000

Paired Samples Effect Sizes

			Standardizer[a]	Point Estimate	95% Confidence Interval	
					Lower	Upper
Pair 1	AsBuilt_Speed - PhoneApp_Speed	Cohen's d	.73694	.824	.474	1.167
		Hedges' correction	.74360	.817	.469	1.157

a. The denominator used in estimating the effect sizes.
Cohen's d uses the sample standard deviation of the mean difference.
Hedges' correction uses the sample standard deviation of the mean difference, plus a correction factor.

Appendix H: Full Spearman Correlation Matrix and KMO Test

Correlations

			Environment	Order	Accepted_Gap_#	Vehicle_Model	Gap_Size	Crossing_Speed	Reaction_to_Last_Vehicle
Spearman's rho	Environment	Correlation Coefficient	1.000	.048	-.629**	.132	-.255**	-.431**	.698**
		Sig. (2-tailed)	.	.593	.000	.142	.004	.000	.000
		N	125	125	125	125	125	125	125
	Order	Correlation Coefficient	.048	1.000	-.076	-.040	.001	.117	.058
		Sig. (2-tailed)	.593	.	.402	.656	.992	.194	.522
		N	125	125	125	125	125	125	125
	Accepted_Gap_#	Correlation Coefficient	-.629**	-.076	1.000	-.150	.226*	.345**	-.600**
		Sig. (2-tailed)	.000	.402	.	.096	.011	.000	.000
		N	125	125	125	125	125	125	125
	Vehicle_Model	Correlation Coefficient	.132	-.040	-.150	1.000	-.119	.035	.120
		Sig. (2-tailed)	.142	.656	.096	.	.186	.700	.184
		N	125	125	125	125	125	125	125
	Gap_Size	Correlation Coefficient	-.255**	.001	.226*	-.119	1.000	.070	-.450**
		Sig. (2-tailed)	.004	.992	.011	.186	.	.440	.000
		N	125	125	125	125	125	125	125
	Crossing_Speed	Correlation Coefficient	-.431**	.117	.345**	.035	.070	1.000	-.209*
		Sig. (2-tailed)	.000	.194	.000	.700	.440	.	.019
		N	125	125	125	125	125	125	125
	Reaction_to_Last_Vehicle	Correlation Coefficient	.698**	.058	-.600**	.120	-.450**	-.209*	1.000
		Sig. (2-tailed)	.000	.522	.000	.184	.000	.019	.
		N	125	125	125	125	125	125	125

**. Correlation is significant at the 0.01 level (2-tailed).

*. Correlation is significant at the 0.05 level (2-tailed).

KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.710
Bartlett's Test of Sphericity	Approx. Chi-Square	239.913
	df	21
	Sig.	.000