UNDERSTANDING VULNERABLE ROAD USER BEHAVIOR AND PERCEPTIONS THROUGH HEART RATE DATA: AN EVALUATION OF ROADWAY DESIGN ALTERNATIVES THROUGH IN-LAB AND IN-FIELD CASE STUDIES

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ABSTRACT

Cyclists and pedestrians represent some of the most vulnerable users (VRUs) of roadway infrastructures. Understanding their behaviors, preferences, and interactions with the environment is critical in order to aid planners, engineers, and decision-makers to promote safer spaces and active mobility. This research presents two case studies in which VRUs' behaviors and their interactions with the built environment were tested with the aid of virtual reality (VR) simulation and wearable sensors for heart rate (HR) data collection, in both in-lab and real-world settings.

The first part of this thesis presents a novel way of studying cyclists' perceptions of bicycle infrastructure design alternatives in a safe and low-cost way using immersive virtual environments modeled after a real-world corridor and a previously validated bike simulator. Three infrastructure scenarios were tested: sharrows, a separated bike lane, and a protected bike lane with flexible delineators. Results of the used multinomial logit model suggest gender, age, and abrupt changes in HR affect cyclists' preferences for bike infrastructure design. Overall, gender emerges as the most practically significant predictor variable for bicycle infrastructure preference, with men more likely to prefer sharrows and women more likely to prefer protected bike lanes. Exploratory analysis also suggests that bicyclists who self-identified as "strong and fearless" are more likely to choose sharrows as the preferred design, while bicyclists who self-identified as "interested but concerned" more often chose the protected bike lane. These results highlight the importance of understanding preferences of not just current cyclists, but potential future cyclists. VR simulation offers a low-cost, safe, and efficient method to understand the preferences of individuals interested but not yet choosing cycling as a mode.

The second part of this thesis presents the experimental design and findings of a pilot naturalistic pedestrian experiment conducted on the main commercial street in Staunton, Virginia. The experiment was designed to measure variations in the pedestrian experience when the corridor is open and closed to vehicular traffic, a distinct opportunity provided by a local initiative to repurpose the corridor. Smart eyeglasses with eye-tracking technology enabled the analysis of pedestrians' gaze, while a smartwatch collecting HR data was used to identify potentially stressful events or stimuli, allowing researchers to retrieve information from the pedestrian perspective. Results show that most of the abrupt changes in HR occur while participants focus their attention on the ground of their walking route and at locations near intersections. This study sets the groundwork for future research on linkages between the experiential dimensions of the urban environment and pedestrian behaviors and physiological reactions.

Through these two case studies, this thesis seeks to add to the limited existing literature related to understanding VRUs' behavior and perception using physiological data, in different infrastructure design contexts. The thesis identifies the value of low-cost wearable sensor technology as well as the challenges with implementing such sensors, both in in-lab and in-field settings, with cyclists and pedestrians.

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CHAPTER 1: INTRODUCTION

Cyclists and pedestrians represent some of the most vulnerable users of roadway infrastructure. Vulnerable road users (VRUs) are defined as those individuals who are most at risk in traffic because they lack a protective shield and sustain a greater risk of severe injury in a collision compared to those in motor vehicles (*1*). Bicyclist fatalities have risen, with 2020 deaths of cyclists in the United States topping 938, higher than any year in recorded history (*2*, *3*), suggesting that cyclists' needs have not been properly accounted for while designing road infrastructure and public policies. Additionally, crashes involving cyclists are underreported (*4–9*) and typically only reported if they are severe (*10*). Studies also show other factors lead to underreporting, such as availability of resources, competing priorities, and political influence, especially when comparing data from different countries (*11*). Therefore, there are limitations to using crash statistics when analyzing cyclist safety. Further, in the United States, walking represents 10.5% of all person trips and is the third most prevalent mode of transportation, only behind the usage of cars and SUVs (*12*). In the past ten years, pedestrian fatalities have steadily increased, reaching 6,516 in 2020, the highest value in recorded history (*3*). In 2020, pedestrian deaths represented 17% of the total fatalities in traffic crashes, with an estimated 55,000 pedestrians injured nationwide (*13*). The vast majority of these fatalities occurred in urban areas (82%). When analyzing the events' locations, 75% of pedestrian fatalities took place at locations not categorized as intersections, 15% at intersections, and 10% at other locations (i.e., roadside/shoulders, bicycle lanes, sidewalk, medians/crossing islands, etc.) (*13*). Steps must be taken to ensure that a safer, more equitable, and sustainable environment for VRUs is provided in order to increase active mobility.

However, understanding VRUs' needs and behaviors poses a challenge due to the dangers involved in on-road testing for data collection. Traditional safety analysis relies on crash rates, in what can be described as a *reactive approach* since crashes need to occur for data to be collected. Safety research has been shifting to a more *proactive approach* in recent years, with tools like virtual reality (VR) being used to test pedestrians and cyclists in various virtual environments modeled after the real world to collect data on their reactions and use of facilities (*14*). The first part of this thesis uses a VR bicycle simulator at the Omni-Reality and Cognition Lab (ORCL) at the University of Virginia (UVA) - which has been previously validated (*15*)- to collect data to understand cyclists' behavior and preferences for three alternative bicycle infrastructure designs on the same corridor. In addition to pre- and post-experiment surveys, participants' physiological responses were collected through heart rate (HR) sensors. Currently, there is little prior research that examines bicyclists' physiological responses in simulation, though physiological data has been examined in driving simulators (*16*). *Real or objective traffic safety* relates to the number of crashes and the resulting fatalities and injuries, while *perceived or subjective safety* is the perception of risk (or lack thereof) in a roadway environment; that is, the psychological reaction (*10*, *11*). This study focuses on perceived safety, since the analysis does not include real crash data, but rather test results obtained in laboratory experiments and secondary data elicited from revealed preference surveys. Prior research shows that increasing cycling mode share is related to higher levels of overall safety, according to the "safety in numbers" effect (*17*, *18*), thereby relating perceived safety directly to objective safety, as shown in prior research (*19*).

Moreover, even though pedestrian wayfinding is a simple, every-day task, it requires attention to traffic signs, signals, social norms, and basic traffic rules (*20*). In a similar manner to understanding cyclists' needs and preferences, there is a need to understand pedestrians' interactions with the built environment in order to aid planners, engineers, and decision-makers to promote safer, walkable spaces for active mobility. With the aid of wearable sensors, researchers can gain insight into pedestrians' attention and what physiological reactions elements in the urban environment may elicit. Stress-inducing elements from the built environment could impact the way in which pedestrians enjoy their surroundings, their perception of walkability, safety, and route choices. In the second part of this thesis, pedestrians' physiological reactions and perceptions of the physical environment were tested on a main commercial street in Staunton, Virginia, on fair weather summer days in which the corridor was open to vehicular traffic, and on days that it was closed to motorized vehicles (giving way to commercial and leisure activities). Eye-tracking data was collected via smart glasses while a smartwatch was used to collect HR data. Further, surveys were used to elicit data on participants' stated preferences and demographic and socio-economic data.

The body of research of the current thesis is focused on the use of simulation and wearable sensors for the analysis of VRUs and is divided into two case studies. The first case study focuses on the following research question: What demographic, social, and physiological data is relevant in predicting urban cycling infrastructure preferences? The second, addresses the existence of associations between the interaction of pedestrians to the built environment, comparing their eye-tracking data and physiological reactions when analyzing the same environment in both open and closed-to-vehicle settings. This second case study aims to answer: what elements in the built environment shape the urban experience for pedestrians, and how do they change when motorized vehicles are involved or removed? As a result of the aforementioned case studies, the strengths and weaknesses in the use of wearable sensors to better understand VRUs and their environments, in both lab settings and in-field tests, are also assessed.

CHAPTER 2: LITERATURE REVIEW

This section summarizes relevant existing literature and is organized into the following broad categories: 1) studies examining perceived safety and cyclist infrastructure preference, 2) measured safety studies of different types of cycling infrastructure, 3) studies analyzing cyclists' safety or comfort using VR simulators, 4) research on pedestrians' HR variability in the built environment, and 5) pedestrian experiments with smart eyewear and eye-tracking technology.

2.1 Cyclist perceived safety

Cycling is perceived as being an unsafe mode of transportation (*18*), especially in urban environments where there is exposure to motorized vehicles (*21*, *22*). Safety is shown to be more highly valued than time as a factor for mode choice (*23*) and safety concerns affect route choices and decisions to cycle (*22*, *24*). Feelings of perceived safety (*19*, *21*, *25–31*), perceptions of risk (*19*, *25*, *29*, *32–42*), and comfort (*43–48*), among others, have been used in perceived safety literature to measure the cycling experience, and have been shown to be related to multiple factors like roadway infrastructure, existing traffic, and cyclists' individual characteristics. Perceptions of safety are in accordance with cyclists' route preferences; high bicycling stress, or low comfortability, is one of the most important factors in choosing cycling as a transportation mode (*33*, *49*). Prior studies show that multi-use pathways, which are physically separated from motorists and include facilities for cyclists and pedestrians, are preferred (*50*, *51*) and perceived as one of the safest types of bike infrastructure, even though their measured risk reduction compared to major streets is low (*33*).

The major contribution to a cyclist's perception of lower risk (*34*), reduced feelings of insecurity or stress (*52*), and higher comfort levels (*43*) is for bike infrastructure to be located off-road or adjacent to road infrastructures (e.g., paths and bicycle boulevards). This is in line with the findings that cyclists' safety concerns are mainly due to riding around motor vehicles (*22*). Particularly, cyclists have strong preferences for riding separately from other forms of traffic (*53*) in dedicated bicycle infrastructure (*23*, *54*, *55*), as such conditions correlate to improved perceptions of safety (*31*) compared to biking on-road without bike lanes (*52*, *53*). Female cyclists have stronger preferences for dedicated bike lanes over their male counterparts (*53*, *56*). The existing literature also demonstrates that safety is a greater concern for female cyclists (*51*), that men find cycling more acceptable (*34*), and that women are more risk-averse (*57*). Moreover, female cyclists have been found to experience higher levels of fear of traffic (*25*), perceptions of risk (*58*, *59*), and discomfort cycling in mixed traffic (*59*) than their male counterparts.

2.2 Safety outcomes for cycling infrastructure

Few studies have examined bicycle crash data relating to different cycling infrastructures (*6*, *9*, *60*, *61*), mainly due to limited empirical data that has insufficient spatial disaggregation. Robartes and Chen found that bicycle crashes involving automobiles on urban or suburban roads with a dedicated bike lane showed a smaller proportion of injuries compared to those occurring on streets with shared bike lanes or with no cycling infrastructure (*9*). Lott and Lott studied the same type of crashes in 1976 from police reports in a California city with bike lanes and compared them to those in another California city with no bike-lane system (*61*). The resulting frequency of crashes was overall reduced by 31% by the apparent effect of bike lanes, up to 53% for certain crash categories. Additionally, Mukoko and Pulugurtha's model of bicycle-vehicle crashes suggested that cyclists are significantly more likely to be involved in crashes while traveling on roadway segments with no bicycle lane (*62*). Finally, the study carried out in Denmark by Myhrmann et al. using single-bicycle crash data obtained from 2010-2015 medical records showed that only 24% of the analyzed crashes occurred on a bike lane, with the remaining taking place on road segments without dedicated bike infrastructure (*60*).

2.3 Cycling tests in VR simulators

Recently, VR simulators and virtual environments have been used as an effective tool for transportation research (*16*, *63–71*) and there have been multiple studies related to the development and validation of bicycle simulators and prototypes (*14*, *72–75*). However, there is little prior research of bicyclists' perceived safety or comfort using VR simulators (*76–79*). Among this small body of existing literature, Nazemi et al. used a bike simulator and immersive VR to test perceived level of safety and willingness to bicycle, along with pre-test and post-test questionnaires (*76*). Results showed that participants felt safer cycling on a segregated bike path than cycling on a striping-separated bike lane on the road and roadside next to vehicles, particularly for non-bicyclists. No significant differences in gender and between different durations of cycling were found. Older participants showed more concerns about roadside cycling, and commuters were more confident in the same facility. Huemer et al. found that a layout with a designated bicycle lane was subjectively safer, more comfortable, and easier to understand for cyclists than other bicycle infrastructure designs (*77*). Furthermore, Cobb et al. used a simulator and measured galvanic skin response (GSR) to conclude that cycling in a bike lane incited less skin reaction than the no-bike lane condition, and those cycling without the bike lane showed more GSR to vehicular volume (*78*). Female cyclists were found to feel less comfortable than males in either scenario, regardless of their biking skills. Finally, Bogacz et al. measured risk perception among cyclists using VR, brain-imaging data, and a dynamic hybrid choice model (*79*). The study tested changes in participants' behavior relating to perceived risk due to changes in traffic conditions and showed behavioral and neural consistency. Changes in the amplitude of a particular brainwave were associated with increased perceived risk and the propensity to brake.

2.4 Heart rate analysis in pedestrians

In experiments unrelated to vulnerable road users, HR has been associated with emotional factors like fear, anxiety, or both (*80*, *81*), and proved to be the best physiological marker for stress assessment (*82*). HR variability refers to the beat-to-beat alterations in human heartbeat (*83*). Researchers have reported HR variability to have a significant positive correlation with subjective situation awareness, as tested in varied simulation training scenarios (*84*, *85*). Regarding pedestrians, stressful environmental factors could have an impact not only on their stress levels, but on their interaction with their surroundings, perceptions of environmental walkability, and route choices. Pedestrians are highly exposed to the dynamics of their environments, more so than those inside motorized vehicles whose experience is mediated by the vehicle itself (*86*).

Incorporating pedestrians' physiological factors into the evaluation of built environments allows for the continuous appraisal of their walkability and identification of features that elicit abnormal physiological responses (*87*). Moreover, HR has been deemed as "quite responsive" to momentary changes in mental workload that are observed in pedestrians (*88*) and has been shown to be indicative of sudden events like a close call with a vehicle or being startled (*86*). On account of noise-increasing mental workload, pedestrians would experience greater psychological stress as the number of (noise-generating) motorized vehicles along their route grows (*86*).

An emerging branch of research incorporates wearables that allow for the collection of participants' physiological factors (*86*). Studies conducted with pedestrians in the built environment, aided by wearable HR sensing devices, showed that road congestion degree (representing traffic congestion and sidewalk width) was an important environmental factor affecting pedestrians' personal mental stress (*89*). For example, LaJeunesse et al. (*86*) measured pedestrians' physiological factors (including HR) during normal walking activities in multiple traffic contexts and concluded that subjects' stress levels were not correlated to particular crossing locations but rather to roadway conditions. When participants walked close to collector and arterial streets, in areas of industrial and mixed land uses, higher levels of stress were detected. More traffic, and thus noise and opportunities for pedestrian-vehicle crashes could explain the intensified stress reactions reported in busier land uses. On the contrary, the authors stated that stress levels were relatively low in lower-density residential areas, parks, forests, university campuses, and in areas with low vehicle traffic. In addition, a 1981 experiment with pedestrians with different levels of visual impairments -from none to blind- showed that increasing familiarity with the walked route tended to result in lower levels of stress (measured through the mean HR and standard deviation), particularly in simple routes (*90*). Furthermore, Kim et al. (*87*) introduced an analysis of body responses (that included HR) to investigate the conditions of a walkable built environment and the interactions of pedestrians' activities and environment features. The authors observed that locations with features regarded as adverse for pedestrians, such as barking dogs, a container for storing gas, a partially-demolished house, and "no sidewalk" zones, had higher HR reserve values -a normalized index mostly used to identify physical demand from HR changes (*91*)-.

2.5 Analysis of pedestrian eye tracking data

Emerging new, smaller, and more portable wearable devices -such as smart glasses, sensors, and cameras- allow researchers to map visual attention and collect data from the first-person perspective (*92*). Until recently, research involving eye-tracking glasses with pedestrians was only possible in lab settings (*93*), mostly due to technological constraints and the complexity of monitoring tasks in their natural environments (*94–97*). However, such technology is now being used more frequently outdoors, providing a deeper understanding of how these users interact with real-life environments (*98*). Hasan and Hasan (*99*) concluded in their 2022 study that most research on pedestrian safety using sensors (and augmented reality) was concentrated on a specific domain, usually not suitable for the real-world setting. Furthermore, experimentation with smart glasses has been identified as needed, in relation to understanding pedestrians' changes in focus as they notice objects during their walking experience (*100*). It has also been identified that using smart glasses for data collection allows researchers to obtain reliable data on pedestrians' behavior in their regular commutes and retrieve most of the information experienced by them (*98*).

Multiple studies were identified on the use of eye-tracking data as a means to explore pedestrians' experiences in outdoor settings in urban environments (*101–107*). Mobile eye-tracking devices are an evolution of lab-based eye tracking that allow researchers to evaluate focus and eye movements while a person is traveling in a real-world environment. Eye tracking data can provide insight into pedestrians' perceptions and cognition as it is a means of studying how visual information is processed (*105*). Researchers have found that pedestrian viewing behavior is highly targeted, since they take cues from the environment that aid them in walking around safely, which suggests that pedestrians intuitively understand what visual cues to focus on, without having to search for them (*103*). In a 2020 study that focused on the visual attention process of pedestrians looking at a particular building, de la Fuente Suarez (*101*) found that time spent looking at the building did not relate to the walked route or its start point. However, facades' high-quality architecture that was described as aesthetically pleasing by participants, was viewed longer. Further, it has been found that street edge ground floors receive more visual engagement than their upper floors, and the visual attention paid by pedestrians to street edges is unequal in non-pedestrianized and pedestrianized streets, having pedestrians focus more on the walked side of the former, and having focus more balanced on both sides of the latter types of streets (*104*). A study found that the walked path and other people were the items most frequently fixated on by pedestrians, with most of the visual attention on the target path happening at close distances, while fixations with people were most likely at far distances (*108*).

2.6 Conclusions from the literature review and paper contributions

The conducted literature review focused on cyclists' perceptions of safety, bicycle infrastructure as it relates to safety, and research conducted with cyclists within in-lab settings aided by bike simulators and VR. As shown, only a few simulator studies of cyclists' perceived safety use physiological data, and only a limited number (exclusively from ORCL at the University of Virginia) have used HR data (*15*, *109–112*). It has been demonstrated in an on-road experiment that situations perceived as risky by cyclists induce higher HR responses (*52*). This thesis contributes to the emerging literature review by analyzing perceived safety of bike infrastructure utilizing HR data in bicycling VR simulation. Further, this literature review included past research on pedestrians' physiological responses (particularly changes in HR) in the built environment, with no laboratory constraints, and studies conducted with the use of smart eyewear and eye-tracking technology. This thesis' contribution to the current state of knowledge with an exploration of the use of wearable sensors' outputs to assess pedestrians' perceptions of real-life settings in an urban environment. Better understanding of bicyclists' and pedestrians' perceptions and interactions with their environment can aid engineers, planners, and decisionmakers in promoting safer and more sustainable modes of transportation.

CHAPTER 3: PHYSIOLOGICAL RESPONSES OF BICYCLISTS IN A LAB VIRTUAL REALITY SIMULATOR: CASE STUDY OF PERCEIVED SAFETY

In this chapter, cyclists' perceptions of bicycle infrastructure alternatives were tested through immersive virtual environments and a previously validated bicycle simulator. The environments were modeled after a real-world corridor and three bicycle infrastructure designs were tested: sharrows (with no bike lane), a separated bike lane, and a protected bike lane with flexible delineators. Data on participants' preferences and background were elicited from surveys, and HR data were collected using smartwatches.

3.1 Methodology

3.1.1 Experimental process

Before starting the biking experiment, participants answered questions designed to elicit sociodemographic data in a pre-test questionnaire and put on two smartwatches (one on each wrist) that measured their HR. Once on the bike simulator, participants completed a familiarization run in VR to get comfortable with the stationary bike's elements: pedals, controllers for braking, and steering. Steering calibration for each participant takes place at this stage. The immersive virtual environments in VR were developed in the Unity 3D game engine, and Stream VR platform using HTC Vive Pro Eye headset and hand-held controllers. Full development of the simulator, components, and testing elements can be found in Guo et al. (*15*). During the experiments, cyclists were exposed to three different scenarios in VR modeled after three blocks on the Water Street corridor between 2nd Street Southwest and 2nd Street Southeast in Charlottesville, Virginia (**Figure 3.1**). Water Street is a two-lane road with parallel parking spaces along the westbound side.

Each immersive virtual scenario represented an alternative bicycle infrastructure design: 1) the as-built scenario (mixed-use roadway with no bike lane and painted sharrows), 2) a separated bike lane along the eastbound lane, and 3) a protected bike lane with flexible delineators, also in the eastbound direction. All other factors between scenarios remained constant (e.g., traffic volume, vehicle speeds, vehicle lane width, etc., details of which can be found in Guo et al. (*109*)). The simulated bike lanes are 5ft wide and other biking infrastructure elements (e.g., spacing between flexible delineators) were designed following Federal Highway Administration standards (*113*).

The order in which participants were immersed in these alternative design scenarios was randomized to avoid possible biases in responses due to the novelty and excitement of cycling in a simulator environment. Each participant cycled in each of the three scenarios once. Following the experiments, participants completed a post-test survey in which they stated their safety perceptions.

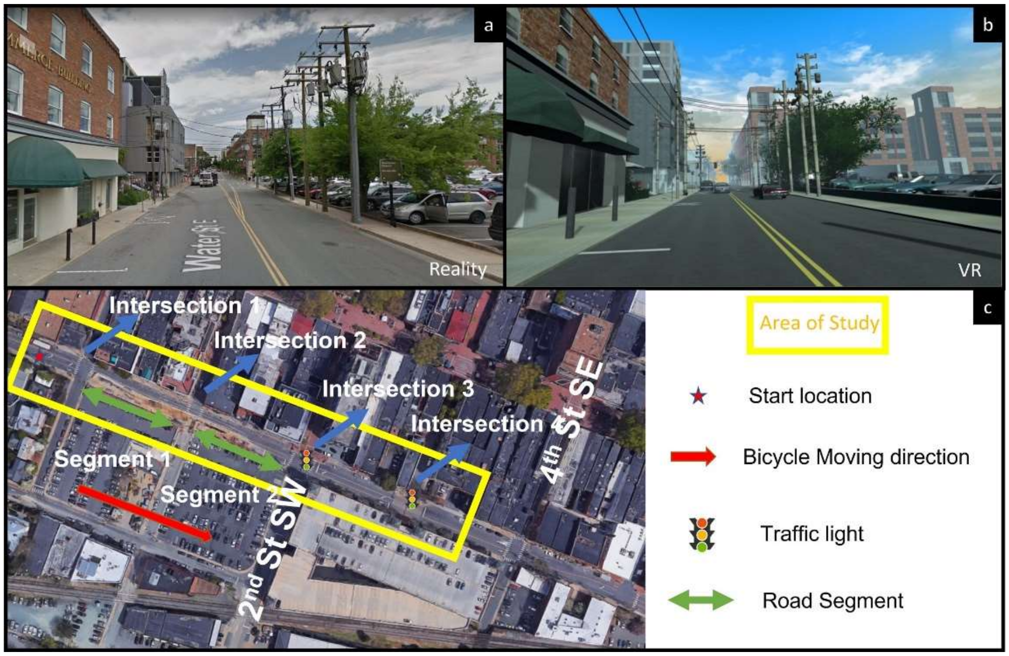

Figure 3.1: (a) Real-life to (b) VR comparison and (c) study area: Water Street corridor in Charlottesville, VA

3.1.2 Participants

Test participants were locally recruited via university email lists and word of mouth. Participants were required to be over 18 and without any health condition that would prevent them from riding a stationary bike or using a VR headset. In the recruitment email, potential participants were warned that glasses may interfere with the use of the VR headset. A total of 14 of the recruited participants reported they wear glasses occasionally or regularly. During testing, no interference between eyeglasses and headsets occurred and all 14 participants were able to complete the experiment. The number of tested participants was 51, but one participant could not finish the experiment due to motion sickness, resulting in a sample size of N=50. All tests were carried out at the ORCL at UVA in February and March of 2021.

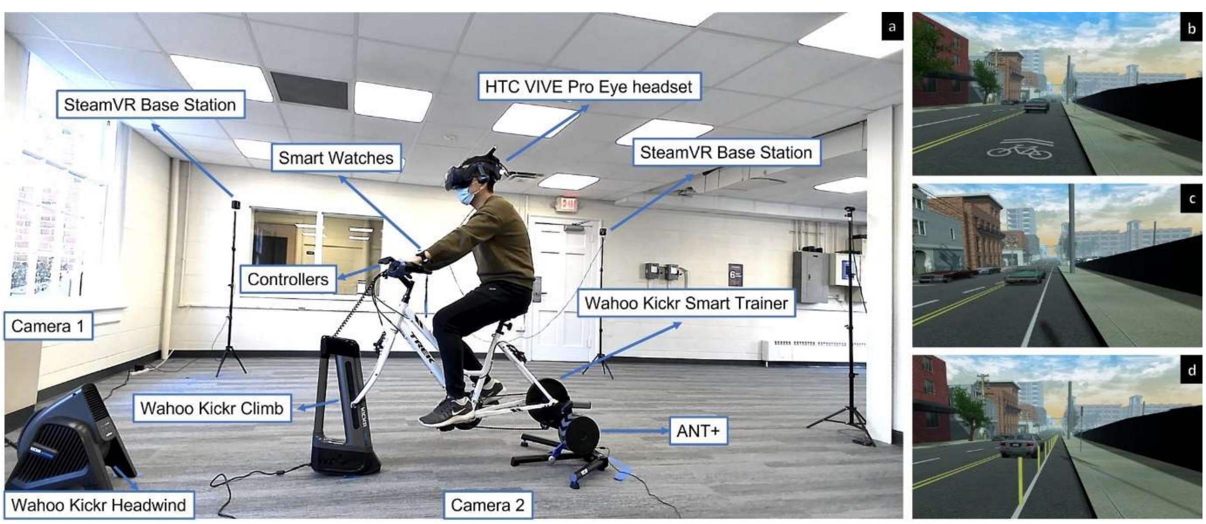

Figure 3.2: (a)VR Bicycle simulator setup and scenarios in the immersive virtual environment (b) sharrows/as-built, (c) separated bike lane, and (d) protected bike lane, respectively)

3.1.3 Data collection

The collected data (N=50) could be categorized into three groups: sociodemographic data, stated preference data, and physiological data. Sociodemographic data were collected from the pre-test surveys; this included population-based factors like gender, age, race/ethnicity, personality traits, and socioeconomic factors like income and educational level. To assess personality traits, the Ten-Item Personality Inventory (TIPI) (*114*) was used to assign scores on the main five personality dimensions that are used as a model for personality (extraversion, agreeableness, conscientiousness, emotional stability, and openness to experience). Participants were asked 10 questions on personality traits that could be answered on a scale from “Strongly agree” to “Strongly disagree”. The TIPI methodology uses a rubric to turn the answers into a numerical score on the main five personality dimensions used to assess personality. Additionally, biking attitude was elicited from participants as a way to group participants in terms of how they view bicycling. The Roger Geller typology characterizes people as one of four types of cyclists concerning their attitude towards biking: strong and fearless, enthused and confident, interested but concerned, and no way, no how (*115*). Revealed infrastructure preferences, elicited from the post-test surveys, included participants’ assigned safety ratings for the different bike infrastructure scenarios (on a scale from 1- “Not safe at all” to 5- “Very safe”). The rating of perceived safety of each infrastructure scenario can be subject to the person’s bias and might pose difficulty for fair comparisons since the values used in the rating (1 through 5) cannot be assumed to be scaled identically across all participants. Therefore, participants were also asked to select which design scenarios are most and least preferred, based on the participant’s perceived safety. The variable representing the physiological response was chosen to be HR changepoints to account for the individual variability across participants’ HRs. HR changepoints are abrupt changes in mathematical expectation, correlation relations or dispersion that result from changes in either external or internal environmental factors (*116*). They measure the progression of each participant’s HRs, not on its absolute value, and isolate points in the time-series data where HR suddenly varies. Through the testing, smartwatches collected HR data with a 1 Hz frequency. *Rising* HR points show the HR changepoints in which the HR reading is higher than the average of the previous five HRs detected, following the methodology by Guo et al. (*109*). To reduce inconsistencies in the results, HR changepoints collected during steering calibration of the bike simulator (that is before the participant starts pedaling) and after the third intersection (at the end of the corridor, where the participant’s stop point is not fixed) were dismissed.

Descriptive statistics for the collected data can be seen below (**Table 3.1**) for the total sample (N=50) used for exploratory analysis and for the reduced smaller sample size used in the explanatory analysis due to missing data (N=42). Missing data can be attributed to sensor malfunction (e.g., participants not having the smartwatch tight enough around their wrists) and participants not willing to disclose some personal information in the surveys (e.g., age).

Table 3.1: Descriptive statistics of the total and reduced samples

Variable	**Total Sample (N=50) (Exploratory Analysis)**	**Reduced Sample (N=42) (Explanatory Analysis)**
Respondent’s socio-economic characteristics		
Gender: Female	46.0%	47.6%
Gender: Male	54.0%	52.4%
Age: 18-29	-	45%
Age: 30-49	-	38%
Age: 50 +	-	17%
Biking attitude: Strong and fearless	18.0%	16.7%

Biking attitude: Enthused and confident	52.0%	50.0%
Biking attitude: Interested but concerned	26.0%	28.6%
Biking attitude: No way, no how	4.0%	4.8%
Educational level: High school/GED	8.0%	7.1%
Educational level: Some college (no degree)	10.0%	9.5%
Educational level: Bachelor's degree	22.0%	21.4%
Educational level: Graduate degree	60.0%	61.9%
Race/ethnicity: White/Caucasian	64.0%	57.1%
Race/ethnicity: Asian/Pacific Islander	30.0%	33.3%
Race/ethnicity: Hispanic/Latino	2.0%	2.4%
Race/ethnicity: Other	6.0%	7.1%
Race/ethnicity: Prefer not to answer	2.0%	2.4%
Personality trait: Extraversion (mean)	3.87	3.88
Personality trait: Agreeableness (mean)	4.98	4.98
Personality trait: Conscientiousness (mean)	5.69	5.67
Personality trait: Emotional Stability (mean)	4.88	4.79
Personality trait: Openness to Experiences (mean)	5.32	5.30

3.2 Results and discussion

The independent variables examined in this study to affect bicycle infrastructure perceived safety include 1) participants' demographic and socioeconomic data, and 2) HR data. The dependent variable (perception of safety) is represented by the safety ratings participants assigned to each infrastructure alternative scenario and safest and least safe scenario rankings.

The empirical analysis was divided into two stages. The first stage was an exploratory analysis that consisted of utilizing multiple methods to summarize the dataset's characteristics, discover patterns and/or outliers, and check assumptions, while the second stage of analysis involved constructing an explanatory model of how demographic, socioeconomic, and physiological data relate to a participant's choice of safest infrastructure design scenario. Both analyses are discussed in detail in this section. N=50 is the sample size starting point, but sample size is adjusted in the different analyses based on available data as explained in the following subsections. For simplification, the three tested scenarios will be hereon referred to as B1: As-built scenario (sharrows with no bike lane), B2: Separated bike lane, and B3: Protected bike lane with flexible delineators.

3.2.1 Exploratory analysis

Participants' stated preferences, as responses to the instruction "Please select the one in which you felt the least safe and the one in which you felt the safest" are presented in **Figure 3.3**. Results revealed that only 8% of participants ranked B1 as the safest scenario (80% regarded it as the least safe), while 22% chose B2 as safest, and 70% stated their preference for B3 as safest.

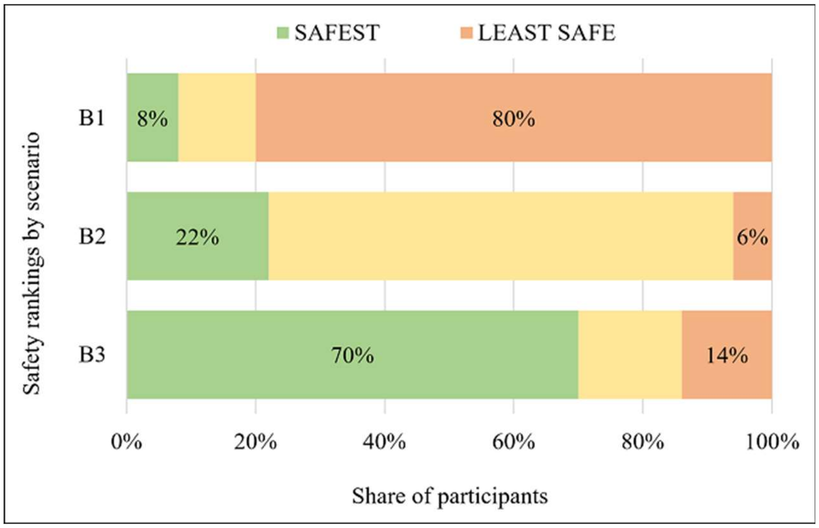

Figure 3.3: Scenario preference (scenario safety rankings) for all participants (N=50)

The boxplot in **Figure 3.4** shows the mean safety ratings for each bike infrastructure scenario for all participants, per the answer to the question "How safe did you feel using the different kinds of bike infrastructure?", on a scale ranging from "1=Not safe at all" to "5=Very safe." The mean rating for B1 was 2.60 (Std. Deviation=1.20, Mode=2) whereas for scenario B2 the mean response was 3.90 (Std. Deviation=0.76, Mode=4), and 4.12 (Std. Deviation=1.10, Mode=5) for B3.

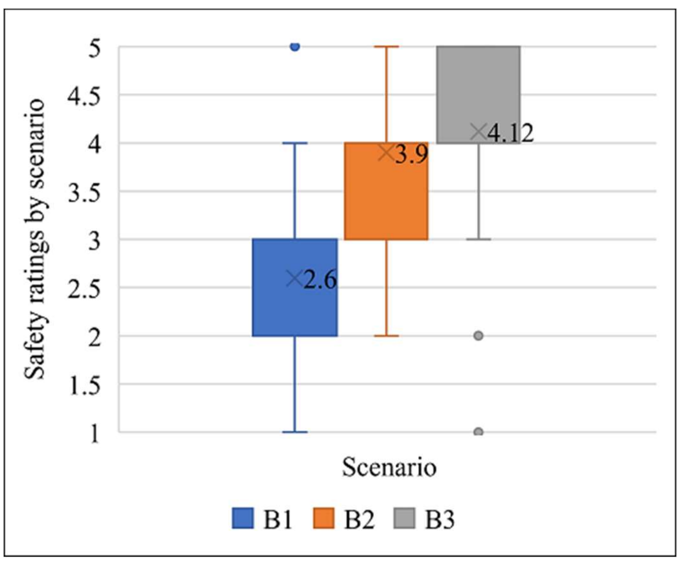

Figure 3.4: Mean scenario safety ratings for all participants (N=50)

Figure 3.4 shows that the protected bike lane (B3) scored higher mean values of safety rating than the separated bike lane (B2) but also showed greater dispersion in results, implying that several participants reacted negatively to biking alongside flexible delineators. Repeated measures ANOVA showed that there were differences between the means of perceived safety ratings in all scenarios ($p=0.000$). Pairwise comparison using Bonferroni correction validates that participants rated B2 higher on average than scenario B1 ($p<0.001$), which translates into a higher feeling of safety provided by biking in the separated bike lane. Furthermore, scenario B3 scored higher mean ratings than B1 ($p<0.001$), indicating that a protected bike lane made participants feel safer than biking in mixed traffic. No statistically significant difference was found between the safety ratings of B2 and B3. These results confirm previous studies' findings that cyclists feel less safe in mixed traffic than in a designated space for biking (*52*, *53*).

3.2.1.1 Grouping variable: gender

The effect of gender on perceived safety was analyzed by grouping the sample by gender and examining the scenario rating responses (**Table 3.2**). In the pre-test questionnaire, participants were asked to choose their gender between "Female", "Male", or "Other." The sample was skewed towards male participants (n_{female}=23, n_{male}=27), but is consistent with cycling tests in reviewed literature (*117*, *118*).

Table 3.2: Descriptive statistics for scenario safety ratings for male and female participants (N=50)

Scenario	Gender	Mean	Std. Dev.	Mode	n
B1: as built	Female	2.17	0.717	2	23
	Male	2.96	1.400	2	27
B2: separated bike lane	Female	3.96	0.767	4	23
	Male	3.85	0.770	4	27
B3: protected bike lane	Female	4.44	0.945	5	23
	Male	3.85	1.167	5	27

The Mann-Whitney U test was used to find whether differences in central tendency between the ratings for both populations exist. The results show that male participants rated scenario B1 more favorably than female participants (p=0.044), and that female participants rated scenario B3 higher than male participants (p=0.045). The results show that the grouping variable "gender" has an impact on the feelings of safety in biking infrastructure alternatives; men seem to report feeling safer than women biking in the as-built scenario with only sharrows, while women feel greater safety biking alongside flexible delineators in a protected bike lane compared to their male counterparts. Additionally, there were no differences in perceived safety ratings between genders for scenario B2. These findings are in congruence with the reviewed literature that indicates female cyclists feel safer than males in separated bike infrastructure (*55*, *119*) and prefer dedicated bike lanes (*53*, *56*) since they experience higher levels of fear of traffic (*25*), perceived risk (56, 57), and discomfort cycling in mixed traffic.

3.2.1.2 Grouping variable: physiological responses

As previously discussed, due to sensor or software malfunction, some participants' HR data were missing or incomplete, which resulted in a sample size of n=43 for HR analysis. Among these 43 participants, the mean for rising HR changepoints was the highest for scenario B1 (mean=0.884) while scenarios B2 and B3 scored mean values of 0.581 and 0.605, respectively. These results indicate that, on average, higher rates of change in participants' HRs could be attributed to cycling in a mixed-use roadway with other motorists, instead of in a designated separated and/or protected lane. This result is consistent with a previous study using on-road testing that exposure to traffic can elicit variations of HR that could be related to higher perceptions of risk, greater physical effort, or both (*52*). **Table 3.3** shows the distribution of participants' rising HR changepoints per infrastructure design scenario. The values show that in the as-built scenario (B1), most participants (74.4%) had at least one rising HR changepoint, whereas, in both bike lane infrastructure alternatives (B2 and B3), half of the participants had no detectable changepoints in their HR (53.5% and 55.8%, respectively). This suggests that a designated space for cyclists could produce lower peaks in HR, leading to a less stressful cycling experience. However, the protected bike lane (B3) scenario produced two rising HR changepoints in 7 participants, more than double the number of participants with two rising HR changepoints for scenario B2. This indicates that some participants had stronger stress reactions biking in the protected bike lane with flexible delineators compared to in a separated bike lane.

Table 3.3: Rising HR changepoint frequency per biking scenario

Scenario	0 HR changepoints	1 HR changepoint	2 HR changepoints	3 HR changepoints	Median	N
B1	11	26	6	0	1	43
B2	23	16	3	1	0	43
B3	24	12	7	0	0	43

A Spearman's correlation test revealed that there was a positive correlation between the safety rating assigned to scenario B1 and the rising HR changepoints for B1 (ρ=0.289, p=0.061), which seemingly contradicts previous findings that environments perceived as high risk by cyclists are likely to produce higher HR than those that are perceived as low risk (*52*). This could be attributed to the fact that rising HR changepoints are derived from a continuous variable. Furthermore, an individual's reaction to a particular infrastructure alternative could be correlated to the reactions for the other two scenarios. In fact, the data showed that there is a positive correlation between an individual's HR changepoints for scenarios B1 and B2 ($p<0.001$). These findings indicate the need to include physiological data in achieving a full understanding of cyclist preferences and behaviors, especially when such data may contradict stated preference data.

3.2.1.3 Grouping variable: biking attitude and personality traits

The Mann-Whitney U test was run to test whether individuals with different biking attitudes rated the three biking scenarios similarly. Participants in the "no way, no how" category were removed from the analysis since the sample size (n=2) was small. For the remaining 48 participants, the results revealed that those in the "strong and fearless" category rated scenario B1 on average more favorably (p=0.039) than others, while those who identify as "interested but concerned" ranked B1 lower than the other participants (p=0.006). This indicates that the grouping variable "biking attitude" affects infrastructure scenario safety ratings. Furthermore, this result supports the notion that participants who were more confident in their biking skills perceived the as-built scenario as safer than others, and those who had some concerns about cycling safety saw the as-built environment as much less safe, highlighting the benefit of simulation-based studies that can capture preferences of potential cyclists (rather than real-world observation studies that only capture preferences of existing cyclists). The results for the "interested but concerned" participants show the potential in designing bicycle infrastructure in a way that can increase mode share, which could then lead to the "safety in numbers" effect for cyclists.

Additionally, a Spearman's correlation test was run to assess correlation between the scores for personality traits and the ratings for safety in the biking scenarios. No statistically significant correlation was found between these variables, although a minor relationship was found between personality trait "emotional stability" and rating for B2 (p=0.149). Moreover, no statistically significant correlations were found between personality traits and physiological responses.

3.2.1.4 Grouping variables: age, education, and income

The age category presented a challenge for analysis due to the size and composition of the sample. The total sample size of those reporting age was n=49 (mean=34.14 years, median=30 years) since one participant did not want to reveal their age. Grouping participants by age using categories like the one used in the US Census would leave categories with little to no participants. Instead, the age variable was treated as a continuous variable for exploratory analysis. A Spearman's correlation test was run between age and scenario ratings. No statistically significant relationship was found between scenarios B1 and B3 and age, but a weak negative relationship was found between age and scenario B2. This result could be attributed to the bias towards younger participants in the sample, due to recruiting practices that relied primarily on the university community. The correlation coefficient is small, and no conclusion can be drawn from this dataset.

In the pre-test questionnaire, participants were asked to choose one category describing their educational attainment out of the following: 1) High School/GED, 2) Some college (no degree), 3) Bachelor's degree, and 4) Graduate degree. Due to the low sample size of the first two categories, they were combined into "High school/Some college". A Spearman's correlation was run between education level and the scenario safety ratings. The results show there was a positive correlation between those with Bachelor's degrees and the safety rating for B1 (p=0.004), a marginal correlation between Bachelor's degree holders and ratings for B2 (p=0.174), a slight negative correlation between the safety rating for B1 and those with graduate degrees (p=0.106). The participant sample is heavily biased towards highly educated participants due to their affiliation with the university (60% of participants have graduate degrees), therefore no conclusions can be drawn at this stage regarding educational level and bicycle infrastructure scenario preferences.

Participants were also asked about their individual or household income, depending on whether they lived with or without roommates. Four participants preferred not to disclose this information and were left out of the sample, resulting in a sample size of n=46 for this analysis. Household income categories were merged into lower income ($0 to $75,000) and higher income (>$75,000) for analysis. The Mann-Whitney U test was used to compare differences in central tendency between the safety ratings of both groups. The findings showed that those in the lower income category ranked scenario B2 higher (p=0.016). Since no conclusion can be drawn at this stage, the grouping variable "income" will be included in the explanatory stage of the analysis.

3.2.1.5 Grouping variable: race/ethnicity

The sample showed little diversity across races/ethnicities, with a vast majority of participants being white/Caucasian (n=32) or Asian/Pacific Islander (n=15). Thus, due to insufficient representation, the variable race/ethnicity was not included as part of the analysis.

3.2.2 Explanatory analysis

A multinomial logistic (MNL) regression was used to model the relationship between the independent variables and the participant's choice for safest infrastructure scenario. The model aimed to examine predictors in cyclists' preferences and assess whether the selection of the safest scenario can be attributed to personal characteristics and physiological responses to biking in the different infrastructure scenarios. The sample size was reduced to N=42 (with descriptive statistics shown in **Table 3.1**), which includes participants with full HR and age data.

The exploratory analysis allowed for some variables to be excluded outright from the explanatory analysis (race/ethnicity). Other variables (biking attitude, educational attainment, income, and personality) were excluded from the preferred model as the result of an iterative process as they were not found to be statistically significant. Because the rising HR changepoints for B1 and B2 emerged as correlated (r=0.568, p<0.001), these variables cannot be both included in the model, and two models for the safest scenario were built with the as-built scenario (B1) as the reference category (See **Table 3.4** and **Table 3.5**). Models 1 and 2 show consistent effects of gender, age, and rising HR changepoints on participants' preferred safest scenario. Model 1, including the physiological responses for the as-built scenario (B1) and the protected bike lane (B3), was slightly preferred due to its better fit, and is used for results discussion and marginal effects analysis. Likelihood ratio tests indicated the individual contribution of the explanatory variables; gender (p=0.069), age (p=0.005), and rising HR changepoints for B3 (p=0.028) had statistically significant impacts on the preference for the safest scenario. The physiological responses for B1 and B2 were near statistical significance at the 90% confidence interval, and are still included in the model due to small sample size.

Table 3.4: Multinomial logit Model 1 results (N=42)[a]

Alternative	B2		B3	
Variable	**Parameter**	**Std. Error**	**Parameter**	**Std. Error**
Alternative specific constant	15.375	9.385	17.372 *	9.321
Gender (reference category: Female)	-3.894	2.770	-4.615 *	2.693
Age	-0.280 *	0.166	-0.278 *	0.163
Rising HR changepoints for B1	3.389	2.349	3.157	2.297
Rising HR changepoints for B3	-3.227	2.111	-3.459 *	2.082
Log-likelihood	49.752 **			
Cox and Snell Pseudo R-Square	0.313			
Nagelkerke Pseudo R-Square	0.396			
McFadden Pseudo R-Square	0.241			

[a] * indicates 10% significance ($p < 0.1$), and ** indicates 5% significance ($p < 0.05$)

Table 3.5: Multinomial logit Model 2 results (N=42)[a]

Alternative	B2		B3	
Variable	**Parameter**	**Std. Error**	**Parameter**	**Std. Error**
Alternative specific constant	12.939 **	6.362	14.842 **	6.272
Gender (reference category: Female)	-3.494	2.315	-4.142 *	2.216
Age	-0.200 **	0.097	-0.199 **	0.093
Rising HR changepoints for B1	2.863	2.157	2.603	2.124
Rising HR changepoints for B3	-3.456 *	1.905	-3.623 *	1.859
Log-likelihood	50.339 *			
Cox and Snell Pseudo R-Square	0.304			
Nagelkerke Pseudo R-Square	0.384			
McFadden Pseudo R-Square	0.232			

[a] * indicates 10% significance ($p < 0.1$), and ** indicates 5% significance ($p < 0.05$)

From both models, it can be inferred that males are less likely than females to choose scenarios B2 and B3 over B1. Additionally, both models suggest increasing age has a negative impact on scenario preferences for B2 and B3 over B1, which implies that older participants tend to find the bike lane scenarios less safe than the as-built scenario. Finally, the rising HR changepoints for scenario B3 indicate cyclists' preferences in biking scenarios: with higher HR changepoints under scenario B3, the models showed that cyclists are less likely to choose scenarios B2 and B3 over B1.

Marginal analyses (based on Model 1) were carried out to better understand the practical significance of the explanatory variables on the outcomes (most preferred infrastructure scenario) and the shifts in probabilities of choosing each scenario. **Table 3.6** includes the default outcome probabilities when all variables are held at their mean, as well as the resulting probabilities from changes in each variable from the preferred model while controlling age at the mean, and physiological responses at the median. To analyze the effect size, a change in gender implies that the reference category changes from female to male, while changes in age were carried out by increasing the mean age by one standard deviation (13.1 years). Rising HR changepoints were increased by 1 discrete changepoint from the median (1 in the case of B1, and 0 for B2 and B3).

Table 3.6: Marginal effects analysis for MNL Model 1 (n=42)[a]

	Probability of choosing B1 as safest	Probability of choosing B2 as safest	Probability of choosing B3 as safest
Model outcome (all variables held at their mean)	0.2%	20.6% **	79.6% **
Model predicted choices (controlling for all other variables)			
If all participants were female	0.0%	13.7%	86.3% **
If all participants were male	0.1%	24.5% **	75.3% **
With 1 STD deviation increase in age	0.6%	18.2% *	81.2% **
With 1 unit increase in rising HR changepoints for B1	0.0%	22.6%	77.4% **
With 1 unit increase in rising HR changepoints for B3	0.4%	22.5% **	77.1% **

[a] * indicates $p < 0.1$ and ** indicates $p < 0.05$

Gender emerged as the most practically significant predictor variable on scenario preference, with the greatest impact on the outcomes' probabilities. If the sample consisted of all women, all other variables held constant, there would be a 6.7% increase in the share of those who choose B3 as the safest scenario. Moreover, higher HR changepoints for B1 and B3, made it less likely for the participant to choose the protected bike lane scenario as safest, more likely to choose the separated lane, and had almost no impact on the choice of B1 as safest. Increases in participants' age resulted in mixed results, showing that older participants tend to choose B2 less as the safest scenario. Further analysis would be needed to fully understand the marginal effects of the physiological responses, especially to comprehend the relationship between rising HR changepoints and gender.

Finally, a model for the choice of least safe scenario was also explored (the resulting parameters can be found in Appendix A.) The same variables (gender, age, and physiological responses for scenario B3) emerged as explanatory, although only for explaining the choice of B3 over B1. There were no statistically significant explanatory variables for the outcome of B2 as the least safe scenario.

CHAPTER 4: PHYSIOLOGICAL RESPONSES OF PEDESTRIANS IN THE REAL WORLD: CASE STUDY OF REPURPOSED URBAN STREET

This chapter includes the experimental design and findings of a pilot naturalistic pedestrian test conducted on the main commercial street of Staunton, Virginia. A local initiative to repurpose the streets on certain days in the week allowed for the experiments to be conducted to measure variations in the pedestrian experience when the corridor is open and closed to vehicular traffic. Smart glasses with eye-tracking technology enabled insight into the pedestrian viewpoint, while physiological data was collected with a smartwatch. The experiment aimed to examine variations in the pedestrian experience of the same corridor, under the two use cases.

1.1 Methodology

4.1.1 Experimental process

This naturalistic pedestrian experiment was designed to have participants walk four blocks on East Beverly Street (between Market Street and Lewis Street), a two-lane, one-way (westbound) corridor with permitted parallel parking along the south side. Beverly Street is the primary commercial street in downtown Staunton, Virginia. Since June of 2020, and as a result of COVID-19 safety measures, Beverly Street has been closed to vehicular traffic, typically April through October, starting Fridays at 4pm until Mondays at 7:30am, as part of the "Shop & Dine Out in Downtown" initiative. Street closures extend a total of four blocks, in the aforementioned segment. While motorized vehicles are restricted from driving on the corridor, all minor streets that cross Beverly Street remain open to traffic. For that purpose, temporary in-ground bollards located along the intersections of the corridor are used to close off the corridor and provide safety and guidance for both drivers and pedestrians. Additionally, official city vehicles typically block street ends (removing access to parallel parking along the corridor), and the City of Staunton makes five local parking garages free of charge when Beverly Street is closed to vehicles. The cross streets along this corridor, Lewis Street, Central Avenue, Augusta Street, New Street, and Market Street, remain open during the closure of Beverley Street. **Figure 3.5** shows Beverly Street in both operational scenarios: while it is open to vehicular traffic and when it is open exclusively to pedestrian traffic.

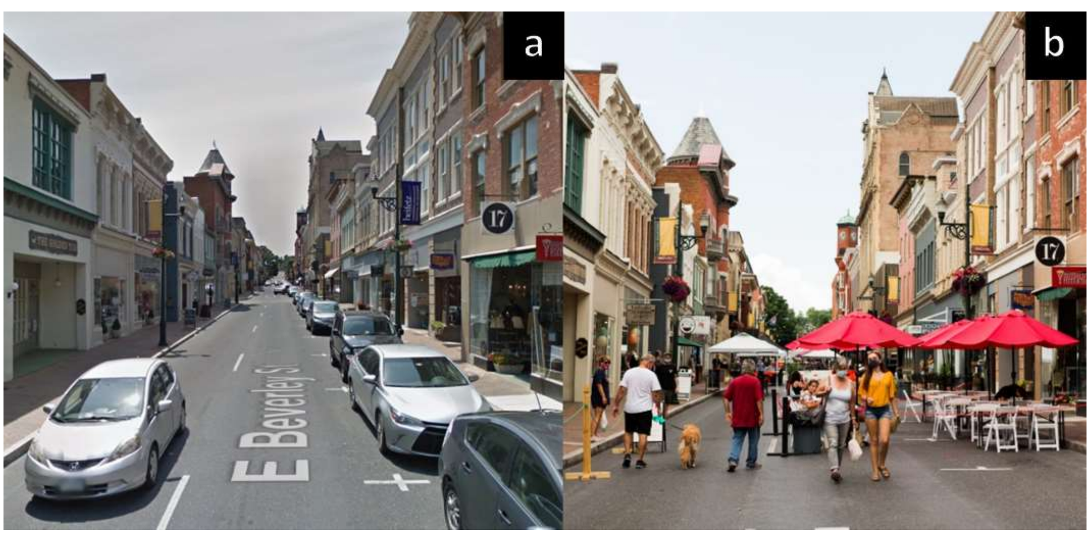

Figure 3.5: (a) Beverly Street while it is open to vehicular traffic (source: Google Streetview) and (b) Beverly Street while it is open to pedestrians only

As a result of this initiative, during times that Beverly Street remained closed to vehicular traffic, multiple shops, restaurants, businesses, and pop-up vendors set up in the street with tents and designated spaces for outdoor dining, cigar smoking, and playing stations for children. The initiative is a measure set by the City of Staunton to support local business owners that could not fully reopen their businesses indoors at the beginning of the COVID-19 pandemic. This approach to street closures is similar to others in the United States and globally, particularly emergent during the pandemic (*120*). Additionally, Beverly Street is only closed to vehicular traffic on weekends, which provided a distinctive opportunity to compare pedestrian behaviors in both an open and closed-to vehicles setting, while many other features of the built environment remained the same.

The conducted experiment included two parts: the first being held on Thursdays, when the Beverly corridor remained open to vehicles, and the second on Fridays, when Beverly Street was reserved for pedestrian-only use. To the extent possible, participants were scheduled at similar times for both tests, between the hours of 4:30 pm to 8:30pm, in order to avoid extreme changes in light conditions between open and closed-to-vehicles scenarios. All tests were carried out during the months of June and July of 2022, while a practice run occurred on Friday, June 3with 5 researchers and city employees.

Prior to their participation, participants were emailed a short description of their tasks in the pedestrian test and participation requisites, including the consent form and pre-test survey eliciting sociodemographic and physical activity data. Participants were instructed to meet with the research group on South Market Street (**Figure 3.6**), in a private patio provided by a local coffee shop, about 75ft. from Beverly Street. A hard copy of the participation consent form was provided for participants to sign and a hard copy of the test route was shown and explained by one of the researchers. Participants' decisions to participate in the study were completely voluntary, and they were free to withdraw from the study at any time. The test route required participants to walk westbound from the intersection of Beverly Street and Market Street to the intersection of Beverly Street and Lewis Street along the southside sidewalk, cross Beverly Street at the intersection with Lewis Street, walk eastbound along the northside sidewalk back to the initial intersection of Beverly Street and Market Street, and cross Beverly Street until the start location of the test was reached (**Figure 3.6**). The pre-defined walking path remained constant throughout the phases of the test, regardless of whether Beverly Street was open or closed to vehicular traffic. The order in which participants walked the open/closed-to-vehicle scenarios was random, to avoid any bias that might emerge from the novelty or excitement of participating in the experiment and mostly depended on participants' availability. Participants could only walk each street scenario once, that is, once on a Thursday and once on a Friday.

Figure 3.6: Study area and walking route on the Beverly Street corridor in Staunton, VA

At the meeting point, after explaining the walking route, researchers assisted the participants with putting on the wearable sensors and briefed them regarding their use. These included the Tobii Pro Glasses 3 smart glasses, whose battery pack was asked to be safely placed in participants' pockets, belt loop, or in their hand before each run, and a Fossil electrocardiogram smartwatch (ECG wristwatch) that was fitted to always ensure contact with the skin or either wrist. The smart glasses have a camera which allows for a first-person view of the participants' surroundings (*20*). The smart glasses also recorded video, sound, and eye-tracking data, while the smartwatch gathered participants' HR. The smart glasses are used to study human processing of visual data through eye movements (*121*), while the smartwatch can be used to detect induced stress and is used to better understand observed behavior in both operational scenarios, as will be further described in the following subsections. Before leaving the meeting point to start the experiment, the smart glasses were calibrated to each participant's eyes to ensure data collection accuracy.

No member of the research team followed the participants as they carried out the experiment, to ensure participants behaved naturally. Once participants returned to the meeting point, they would return the mobile sensing equipment, and complete a post-test survey once they had completed both phases of the test, that is, walking the predetermined path when Beverly Street was open and closed to vehicles. If asked, researchers did not disclose the aim of the test until the end of both phases, to avoid sharing any information that could cue participants into sharing biased answers in their post-test surveys. Additionally, weather and outdoor conditions were important factors in the completion of the tests, not only because drizzle or rain would obstruct the view through the smart glasses' lenses or possibly ruin the equipment, but because shops and restaurants would not set up furniture and tents outside, even if vehicular traffic was restricted on Beverly Street, which would introduce major changes in the urban environment and preclude experimentation. Participants were emailed at least 24 hours in advance in the event of adverse weather conditions for rescheduling.

4.1.2 Participants

Recruitment for the experiment took place via email within the Staunton area, in identified interest groups, such as Pedestrian or Bicyclist Action Committees, universities, businesses along the corridor of interest, social media, and word of mouth with the help of employees of the City of Staunton. Additionally, a volunteer flyer was distributed in the area to locally recruit participants. It was requested that participants were at least 18 years of age and that they did not wear glasses on the days of the test (if needed, they were asked to wear contact lenses) as the smart glasses could not be put on regular eyewear. Participants who could not walk without assistance were excluded from the study, since the navigation and behaviors of pedestrians with disabilities in urban environments were considered out of the scope of the study. The resulting sample size, or number of participants who completed both phases of the test, was N=12 (n_{female}=8, n_{male}=4, mean age=42.8, Std. dev. age=14.0).

4.1.3 Data collection

As described in the previous section, participants walked on Beverly Street to and from the meeting point. The smart glasses collected a total of 24 recordings (2 per participant), including multiple variables relating to the eyes' position, pupil size, and movement. These glasses are equipped with a forward-facing point-of-view camera with recording resolution of 1920 x 1080 pixels, a sampling rate of 25 frames per second, and a diagonal field of view of 106 degrees (a smaller field of view than the human eye). Generally speaking, it can portray the surrounding on which a pedestrian is focusing their attention (*20*). Further recording capabilities of the glasses include 16-bit mono audio recording, gyroscope, and accelerometer, with movements sampled at 100 Hz.

People interact with their environment through their eyes, and it has been shown that people direct their eyes towards what they are working on (*122*). Gaze has been defined as the analysis of eye tracking data with respect to the visual scene (*123*). A visual fixation is a period of time in which visual gaze remains focused on a specific location (*124*). Thus, gaze focus (or fixations) are critical for understanding the first-person perspective and the interactions between the individual and their surrounding environment, including the built environment and any social interaction that might occur in it. For the purposes of this study, the focus of the analysis will be on gaze data and video recordings (with their corresponding surrounding audio) in order to identify relationships between participants' attention and their physiological responses. The Tobii Pro software was used to analyze the video recordings and showed instances in which the eye is focused on an element (fixation). However, fixation data is not continuously recorded throughout the video recording as it depends on the fit of the smart glasses and the shape of the participants' faces.

Further, instantaneous HR data was collected from the smartwatch as participants completed the test runs (2 per participant) with a maximum frequency of 1 Hz. Consistent with the analysis in Chapter 3, rising HR changepoints were used for physiological response analysis. HR changepoints identify instances in the time-series data with abrupt rising changes in mathematical expectation, correlation relations, or dispersion, as introduced in the previous chapter and explained by the methodology by Guo et al. (*109*). Rising HR changepoints were only considered if they occurred along the predetermined walking path (Beverly Street corridor), dismissing any data points that occurred from the moment participants started the smartwatch recording until they turned on Beverly Street, and the final stretch between the end of the predetermined path and the meeting point. In order to account for uncertainties and the variability of testing in an uncontrolled natural setting, two tolerances (0.000001 and 0.0000001) were tested in the Bayesian changepoint detection codes used to extract the rising HR changepoints from the instantaneous HR readings. This resulted in two different sets of rising HR changepoints, which were compared and condensed by observing the times in which they occurred. If the identified rising HR changepoints were less than 5 seconds apart in each participant's HR time-series data, they were considered a stressful event and the event starting time was matched to the participants' fixation data. Rising HR changepoints that were not detected by both runs were dismissed, as the code itself (intended for laboratory settings) might be too sensitive for a naturalistic setting. The analysis was conducted to ensure that rising HR changepoints corresponded to stressful situations, although physical activity also affects HR. For reference, the pre-determined walking path is mostly flat, with an altitude change of 16 ft. (as measured by Google Maps).

Table 3.7 shows the descriptive statistics for the collected data, including the total sample collected for all participants (N=12), the samples corresponding to the open-to-vehicles scenario, and the ones corresponding to the closed-to-vehicles scenario. The resulting samples do not show 12 participants in each phase of the study due to data loss. HR data loss can be attributed to the smartwatch not having proper contact with the participant's skin, errors either in the smartwatch itself, or the HR uploading process from the watch to the server where the data is stored. Out of the total 15 HR recordings, 11 corresponded to the open-to-vehicles scenario (on Thursdays) and 4 to the closed-to-vehicles scenario (on Fridays). The variables shown in **Table 3.7** were elicited from the pre-test questionnaire and included gender, age ranges, educational attainment, race/ethnicity, and employment status. Finally, participants were asked if they had any visual impairments. Five participants reported vision impairments that included glasses for seeing in the distance, occasional blurry vision, and regular nearsightedness, although no participant reported being color blind.

Table 3.7: Descriptive statistics of the total and reduced data samples

Variable	Total sample (N=12)	Thursday (open) sample (n=11)	Friday (closed) sample (n=4)
Respondent's socio-economic characteristics			
Gender: Female	66.7%	63.6%	75.0%
Gender: Male	33.3%	36.4%	25.0%
Age: 18-29	8.3%	9.1%	0.0%
Age: 30-49	50.0%	54.5%	100%
Age: 50 +	41.7%	36.4%	0.0%
Educational level: High School/GED	0.0%	0.0%	0.0%
Educational level: Some college (no degree)	8.3%	9.1%	0.0%
Educational level: Bachelor's degree	41.7%	36.4%	50.0%
Educational level: Graduate degree	50.0%	54.5%	50.0%
Race/ethnicity: White/Caucasian	85.7%	91.7%	66.7%
Race/ethnicity: Asian/Pacific Islander	7.1%	0.0%	16.7%
Race/ethnicity: Hispanic/Latino	7.1%	8.3%	16.7%
Employment status: Employed full-time	50.0%	54.5%	75.0%
Employment status: Working part-time	25.0%	18.2%	0.0%
Employment status: Student	8.3%	9.1%	25.0%
Employment status: Self-employed	8.3%	9.1%	0.0%
Employment status: Unemployed	8.3%	0.0%	0.0%

4.2 Results and discussion

The combination of gaze, video recording, and rising HR changepoint data allowed for the identification of stressful events in the participants' walks. However, due to sensor malfunction and data loss during the uploading and recording of the HR data from the smartwatch, the initial goal of comparing pedestrian behavior and physiological reactions as they navigated through the urban environment during the open and closed-to-vehicles scenarios could not be pursued. Nevertheless, the analysis focused on identifying occurrences during participants' walks that resulted in physiological reactions, with the advantage that data collected in a natural setting is more advantageous in accurately describing behavior than if it were collected in a controlled environment (*20*).

42 rising HR changepoints emerged from the collected data and the aforementioned analysis. Out of the 42 data points, 33 could be matched with gaze data from the smart glasses recording since gaze data was not available or not continuously recorded by the smart glasses, due to fit to each participant's face and eyes. For each of these 33 data points, the entire minute within which the rising HR changepoint occurred was analyzed, to account for multiple elements in the urban environment that participants could be focusing on, as well as additional time to consider external stimuli.

An area of interest (AOI) is defined as the region that may be observed in a scene or object and allow the eye tracking data to be linked to those segments or objects (*101*). From the video recordings, physical elements that gained participants' visual attention were manually classified into one of the following urban typologies: 1) parked vehicles, 2) moving vehicles, 3) people, 4) store set up outside, 5) traffic lights, 6) traffic signs, 7) storefronts, 8) store frame signs on sidewalks, 9) street furniture e.g., trashcans), 10) floor, 11) natural elements (e.g., vegetation, sky) 12) buildings (upward, excluding storefronts), and a final category that considers 13) random or impossible-to-discern points. Because more than one AOI could have been within the participants' gaze focus during the HR changepoint, the total number of points in each category totals 44 and can be found on **Table 3.8**. Further, using the obtained video data, participants' estimated locations were retrieved and were classified into the following: 1) midblock, 2) end of block, 3) middle of the street (on pavement), and 4) beginning of the block. To analyze the location in which rising HR changepoints occurred, the total 42 data points were used, since fixation data was needed in this instance. **Table 3.9** shows the physical location of the participants when the rising HR changepoints were detected.

Table 3.8: Rising HR changepoints for each fixation category (n=44)

Fixation categories	**Number of detected rising HR changepoints**		
	Total sample	**Thursday (open) sample (n=35)**	**Friday (closed) sample (n=9)**
Parked vehicles	2 (4.5%)	1 (2.9%)	1 (11.1%)
Moving vehicles	1 (2.3%)	1 (2.9%)	0 (0.0%)
People	2 (4.5%)	2 (5.7%)	0 (0.0%)
Store set up outside	0 (0.0%)	0 (0.0%)	0 (0.0%)
Traffic lights	3 (6.8%)	3 (8.6%)	0 (0.0%)
Traffic signs	0 (0.0%)	0 (0.0%)	0 (0.0%)
Storefronts	5 (11.4%)	4 (11.4%)	1 (11.1%)
Store frame signs on sidewalk	1 (2.3%)	1 (2.9%)	0 (0.0%)
Street furniture (e.g., trashcans)	4 (9.1%)	3 (8.6%)	1 (11.1%)
Ground	19 (43.2%)	14 (40.0%)	5 (55.6%)
Natural elements (e.g., vegetation, sky)	3 (6.8%)	3 (8.6%)	0 (0.0%)
Buildings (upward, excluding storefronts)	4 (9.1%)	3 (8.6%)	1 (11.1%)
Random or impossible to discern	0 (0.0%)	0 (0.0%)	0 (0.0%)

Table 3.9: Rising HR changepoints and participant location (n=42)

Location	**Number of detected rising HR changepoints**		
	Total sample	**Thursday (open) sample (n=33)**	**Friday (closed) Sample (n=9)**
Midblock	22 (52.4%)	17 (51.5%)	5 (55.6%)
End of block	11 (26.2%)	8 (24.2%)	3 (33.3%)
Middle of the street	5 (11.9%)	4 (12.1%)	1 (11.1%)
Beginning of the block	4 (9.5%)	4 (12.1%)	0 (0.0%)

43.2% of all rising HR changepoints in the data set coincided with fixation, and thereby could be associated with an AOI. Results showed that the walking path (ground) is the most prevalent AOI which coincides with rising HR changepoints. In the open-to-vehicles scenario, 40.0% of rising HR changepoints associated with AOIs involved participants looking the ground. Similarly, 55.6% of rising R changepoints were associated with participants looking at the ground in the closed-to-vehicles scenario. This result showed that gaze focus was not a good predictor for abrupt HR changes, since it has been shown that the walked path was one of the elements most fixated on by pedestrians (*108*). The categorization when analyzing participants' position could be merged into detected rising HR changepoints that occurred either when the participants were walking (midblock) or engaging in the activity of crossing a street (end of block, middle of the street, and beginning of the block). As a result, for all participants, 52.4% of HR changepoints would correspond to walking (midblock) and 47.6% to crossing an intersecting street. For the open-to-vehicles scenario, 51.5% of rising HR changepoints occurred walking midblock and 48.5% before, during, or after crossing. Finally, for the scenario in which

Beverly Steet was closed to vehicular traffic, 55.6% of rising HR changepoints corresponded to walking midblock and 44.4% to engaging in crossing a street. This showed that, even though areas near intersections represented a small portion in the total length of walked path, the crossing activity accounted for a considerable percentage of rising HR changepoints, related to factors like fear and/or anxiety (*80*, *81*). The anticipation of starting to cross a street, the act of looking one way or both ways for oncoming traffic when applicable, the actual crossing activity, and reaching the opposite block could be categorized as more stress-inducing activities than walking midblock alongside storefronts based on the results. Additionally, rising HR changepoints that occurred during the crossing activity were disaggregated considering if the street being crossed had vehicular traffic or if it was restricted. As a result, 19 (95%) of the rising HR change points corresponded to crossing streets that were open to vehicles, with only 1 (5%) corresponding to physiological responses while crossing a street with vehicular restrictions (Beverly Street). However, it is important to note that as a result of the test's design, most crossings in the pre-determined path entailed crossing roads open to vehicles (minor roads in both phases of the study, and Beverly Street on Thursdays).

Further, the existence of external stimuli that coincided with rising HR changepoints was considered from the video recordings and surrounding audio. This included events that occurred during the experiments such as participants stopping to read a sign at a storefront, a vehicle driving past the participant or turning while they crossed the street, noise from a person raising their voice as the participant was in proximity, or someone shutting a car door, and other pedestrians walking or standing on the same sidewalk. About a third of the abrupt changes in HR could be associated with external stimuli, although this result was subject to the researcher's interpretation of video data and thus cannot support any robust conclusions.

CHAPTER 5: CONCLUSION

5.1 Summary of results

The current research presented two case studies in which VRUs' behaviors and their interactions with the built/virtual environment(s) were examined with the help of wearable sensors (i.e., VR headset for immersive virtual environments, electrocardiogram smartwatch (ECG wristwatch) for instantaneous HR collection, and smart glasses for eye tracking), in both in-lab and in-field settings.

The first part of the thesis presented a novel way of studying cyclist behaviors in a safe and low-cost way using VR simulation, stated preference data elicited from surveys, and physiological responses collected with low-cost HR sensors. Understanding cyclists' preferences is critical for developing roadway designs that ensure cyclists feel safe, and to increase bike mode share since feelings of safety entice more people to ride (*17*, *18*). Using immersive virtual environments, the as-built scenario with sharrows, an alternate scenario with a separated bike lane, and another alternate scenario with a protected bike lane with flexible delineators were tested. This type of study could be used to relate perceived safety to actual safety, of special interest considering the few existing papers that focus on crash data disaggregated by type of bicycling infrastructure.

This study found that the overall perception of safety while cycling on a separated or protected bike lane is higher than while cycling in mixed traffic, which aligned with previous research (*31*, *52*, *53*). Additionally, the protected bike lane with flexible delineators scored higher mean safety values than the separated bike lane and was selected as the safest infrastructure by most participants. Of the variables examined, gender had the greatest impact on safety perceptions. Consistent with previous studies (*25*, *34*, *55*, *58*, *59*, *119*), results suggested male participants felt safer than female participants in the as-built/sharrows scenario, and women's perceived safety of the protected bike lane was higher than that of men. Moreover, biking attitude was shown to be correlated with the perception of safety in the different infrastructure design alternatives. Cyclists who were more assertive in their biking skills ("strong and fearless") perceive cycling in mixed traffic as safer than others, and those who had interest but some concerns about cycling perceived the as-built/sharrows design as less safe. Attending to the needs of cyclists who self-identify as "interested but concerned" could result in increases in cycling mode share. Such preferences could not be captured with on-road testing and data collection of only existing cyclists; however, simulation allows people who are not current cyclists to be included in the dataset.

This thesis also showed that cycling in the as-built/sharrows scenario, instead of in a designated separated and/or protected lane, correlated with more abrupt changes in HR, linked to fear, anxiety, or both (*80*, *81*). Almost three quarters of participants experienced rising HR changepoints in the as-built scenario, compared to half in the separated or protected bike lane scenarios. However, the physiological responses of participants in the protected bike lane indicated that a small but not insignificant number of participants reacted more negatively to biking alongside flexible delineators. Additionally, the preferred MNL model suggested that gender, age, and physiological responses while cycling in the protected bike lane are associated with which biking infrastructure alternative (either a separate bike lane or a protected bike lane) cyclists are more likely to choose over the as-built scenario (sharrows). Gender emerged as the variable with the greatest impact on cyclists' preferences.

The second part of the thesis presented the design of a naturalistic pedestrian test to understand pedestrians' interaction with the built environment in urban settings, taking advantage of a distinct opportunity to compare pedestrian behaviors in both an open and closed-to-vehicles setting. This opportunity was presented by the "Shop & Dine Out in Downtown" initiative in the main commercial corridor in the city of Staunton, Virginia. By incorporating pedestrians' physiological factors (namely, HR), the environment's features that produce abnormal physiological responses could be evaluated (*87*), while the use of smart glasses allowed for data on the visual exploration process, with eye-tracking technology enabling insight into pedestrians' perceptions and cognition (*105*).

Out of the thirteen analyzed AOIs, the obtained results showed that most physiological responses occurred while the participants were focusing their gaze on the ground (or walking path). This could be understood as in congruence with past results showing that street edge ground floors receive more visual engagement than their upper floors (*104*), since 43.2% of the measured physiological responses occurred while looking at the ground, 11.4% at the storefront, and 9.1% while looking upwards at buildings. Further, when analyzing the pedestrians' position relative to the street location, almost half of abrupt rising changes in HR occurred when participants engaged in crossing a street (47.6%). Since intersections represent a small proportion in the total length of walked path, this finding could be related to previous research findings on crossing locations stating that traffic and thus, noise and opportunities for pedestrian-vehicle crashes, could explain the intensified stress reactions (*86*). Other external stimuli, such as loud noises, discomfort generated due to invasion of personal space, or presence or noise from vehicles driving past the participant or turning into their route (*86*), even if not being the focus of participant's gaze, were found to be the cause of a third of the rising HR changepoints. However, it is important to note that the definition of what could be triggering external stimuli for each participant was based on researcher's interpretation of the video data.

This thesis contributes to the state of knowledge by providing a framework for experiment and analysis to understand the perceived safety and preference of bike infrastructure alternatives in VR simulation that can be replicated for multiple locations and infrastructure designs. It should be noted that the inclusion of demographic and socioeconomic variables in the analysis and explanatory model indicate that the method should be adapted for use with location-specific data (*34*). This research seeks to add to the small existing body of literature related to bicycle simulators and immersive VR, with the addition of the collection of bicyclists' physiological responses (HR data) in simulation, mostly examined in driving simulation tests (*16*). Further, the current thesis' contribution includes the design of an in-field naturalistic walking experiment that builds on physiological research and exploration of the use of physiological responses and wearable sensors' outputs to assess real-world settings in an urban environment from the pedestrians' viewpoint.

Overall, the thesis presents the use of physiological data collected from mobile sensors to understand vulnerable road user behavior, in both lab and natural settings. VRUs are more exposed to elements in the built environment while navigating them than any other roadway user since they lack the protective vehicle. This thesis demonstrated through two distinct case studies that use of mobile wearable sensors can contribute to a better understanding of VRUs' sense of stress when evaluating roadway infrastructure alternatives, in both laboratory and field settings. The experiments conducted used low-cost technology and commercially available sensors that proved indicative of cyclists and pedestrians' behaviors and perceptions. Both case studies showed that HR data can provide insight into VRUs behavior and perceptions and can complement data collected from stated preference surveys and other sensors (such as eye-tracking smart glasses or VR headsets).

5.2 Study limitations and future work

The case studies presented in this thesis presented several advantages and limitations associated with using simulation and/or portable wearable devices for studying cyclists and pedestrians. The advantages of using VR include the low-cost, efficient, and safe way of testing cyclists in immersive virtual environments, and the easy inclusion of collection of physiological data for analyzing cyclist behavior while in VR. Additionally, simulation allows people who are not current cyclists to be included in the dataset. The identified limitations are primarily related to the sample in the study. The bike study sample showed biases in representation in educational attainment, age, and race. This is primarily due to the smaller sample size and the fact that participants were recruited locally in a college town with a higher share of younger, highly educated people. Furthermore, testing with the bike simulator was carried out in person during the COVID-19 pandemic (February and March 2021), in a time of heightened sensitivity, which potentially hindered participant recruitment. Testing at the time also meant having constraints about the number of people that could be in the lab and the time required between participants. Future studies should include larger and more diverse samples and explore other variables that may impact cyclists' perceived safety and preferences, such as primary trip purpose. Another factor to be considered in the study's limitations is the use of self-assessed typologies (Roger Geller's "Four Types of Cyclists" and the Ten Item Personality Inventory). Even though self-assessments provide insight into participants' attitude towards biking and personality traits, they have been shown to have shortcomings. Researchers have found that interest in cycling is not always consistent with real riding behavior (*125*, *126*) (i.e., some cyclist in the interested but concerned category were found to not be interested in cycling more (*125*)), and that a higher proportion of strong and fearless riders were classified as non-cyclists, compared to enthused and confident and interested but concerned (*126*). Additionally, the TIPI's design was not intended to meet high standards of reliability. Rather, it was designed to be a brief instrument to assess the main five personality dimensions that are used as a model for personality that optimized validity, where very short measures are needed, and personality is not the research's focus (*127*). A personality typology might not reflect that personalities can change over time or given the context. Finally, it is important to note the limitation in statistical significance associated with the tested sample size. A sample size of 50 participants was settled on considering time and budget limitations of the project, as well as comparable sample sizes used in previous similar studies (*77–79*), although larger (and more diverse and representative) sample sizes would improve the generalizability of the findings (*79*).

The use of wearable devices (smart glasses with eye-tracking technology and electrocardiogram smartwatch) can capture the pedestrian perspective in a built urban environment, which has been identified in previous research as challenging to capture and quantify (*104*). The collection and analysis of video recordings from the smart glasses' camera allows for a first-person view of the participants' surroundings and, as a result, is favorable to interpret surroundings from their point of view (*20*). Additionally, data collection in an activity's native environment has been shown to describe behavior more accurately than that collected in a controlled setting (*20*). An identified limitation is that wearing the mobile wearable devices could be stressful in itself for some participants (*128*), which would affect physiological responses. Further, the use of smart glasses with cameras could elicit privacy concerns for individuals not involved in testing that get recorded (*129*). Additional limitations are primarily related to the data and its exploratory analysis. Instantaneous HR data loss was an important factor in the pedestrian analysis, attributable to errors either in the smartwatch recording, its contact with participants' skin, or the HR uploading process from the watch to the server where the data is stored, which left a reduced sample size from the already small sample of 12 participants in the pedestrian experiment. These sensors, even though mobile in nature, showed some difficulties when experimentation was carried out in the real world, with HR data loss presenting the biggest challenge. It should be noted that even in the laboratory setting, instantaneous HR data loss occurred. This proves challenging when trying to reach concrete conclusions, since they are based on the interpretation of partial data.

Mobile wearable sensors are a promising technology in improving the understanding of vulnerable road users by providing easy-to-obtain data and being flexible in their application (for in-lab or in-field settings). However, there is not a standardized data processing technique or methodology for this type of analysis that would prove valid across multiple experiments. Further research should define standardized methodologies for physiological data analysis and interpretation in the transportation domain. In addition, researcher's bias when identifying pedestrian stimuli from recordings and the limitations in identifying participants' positions from video recordings (instead of more accurate GPS) should be noted. Further research could include the analysis of pupil diameter in experiments that evaluate different roadway infrastructure alternatives. Pupil diameter analysis has been used to estimate pedestrian's mental workload and/or behaviors in the built environment (*107*, *130*) but has not applied to understanding VRUs' reactions to roadway design alternatives.

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APPENDIX A – Multinomial logit Model for the Least Safe Scenario (N=42)[a]

Alternative	B2		B3	
Variable	**Parameter**	**Std. Error**	**Parameter**	**Std. Error**
Alternative specific constant	0.309	3.672	-9.708 **	3.359
Gender (reference category: Female)	0.960	1.488	2.527 *	1.417
Age	-0.209	0.185	0.132 **	0.055
Rising HR changepoints for B1	1.796	1.759	-0.026	1.002
Rising HR changepoints for B2	0.249	0.986	-0.331	0.947
Rising HR changepoints for B3	0.229	0.999	2.246 **	1.078
Log-likelihood	38.841 **			
Cox and Snell Pseudo R-Square	0.371			
Nagelkerke Pseudo R-Square	0.494			
McFadden Pseudo R-Square	0.334			

[a] * indicates 10% significance ($p < 0.1$), and ** indicates 5% significance ($p < 0.05$)

APPENDIX B – Pre-experiment questionnaire (bicycle simulator VR test)

Please provide the participant number given to you in your experiment confirmation email

How did you hear about this study? - Selected Choice
- Word of mouth
- Social media
- Other: ______________

In the past week, have you _______ (please check all that apply)
- Walked to a destination or walked for recreation/exercise?
- Driven or ridden in an automobile?
- Ridden a bike?
- Taken transit?

Approximately how many miles did you walk last week?

Approximately how many miles did you bike last week?

Approximately how many miles did you travel by transit last week?

Approximately how many miles did you travel by automobile last week?

What describes your attitude toward biking? - Selected Choice
- "Strong and Fearless" - I will ride anywhere, no matter the facilities provided
- "Enthused and Confident" -I like to ride and will do so with dedicated infrastructure
- "Interested but Concerned" - I like the idea of riding but have concerns
- "No way, no how" - I do not ride a bike

Do you have any experience with virtual reality headsets?

Here are a number of personality traits that may or may not apply to you. Please indicate the extent to which you agree or disagree with that statement. You should rate the extent to which the pair of traits applies to you, even if one characteristic applies more strongly than the other.
- Extraverted, enthusiastic
  - Agree
  - Somewhat agree
  - Neither agree nor disagree
  - Somewhat disagree
  - Disagree
- Critical, quarrelsome
  - Agree
  - Somewhat agree
  - Neither agree nor disagree
  - Somewhat disagree
  - Disagree
- Dependable, self-disciplined
  - Agree
  - Somewhat agree
  - Neither agree nor disagree
  - Somewhat disagree
  - Disagree
- Anxious, easily upset
  - Agree
  - Somewhat agree
  - Neither agree nor disagree
  - Somewhat disagree
  - Disagree
- Open to new experiences, complex

Agree
Somewhat agree
Neither agree nor disagree
Somewhat disagree
Disagree
Reserved, quiet
Agree
Somewhat agree
Neither agree nor disagree
Somewhat disagree
Disagree
Sympathetic, warm
Agree
Somewhat agree
Neither agree nor disagree
Somewhat disagree
Disagree
Disorganized, careless
Agree
Somewhat agree
Neither agree nor disagree
Somewhat disagree
Disagree
Calm, emotionally stable
Agree
Somewhat agree
Neither agree nor disagree
Somewhat disagree
Disagree
Conventional, uncreative
Agree
Somewhat agree
Neither agree nor disagree
Somewhat disagree
Disagree

The following questions ask you about the amount of time you devote to different activities each day.
On average, how many hours of physical activity do you have each day? - Hours + Minutes
On average how many hours a day do you use a smartphone? - Hours + Minutes
On average how many hours do you spend outdoors each day? - Hours + Minutes

Do you have any visual impairments? - Selected Choice
Yes - please explain here: _______________
No

Are you color blind?

What is your current employment status? - Selected Choice
Employed full-time
Unemployed
Student
Self-employed
Working part time
Retired
Other: _______________

What is the highest educational degree you have earned?

- Less than high school diploma
- High school/GED
- Bachelor's degree
- Some college (no degree)
- Graduate degree

Do you live in a college dormitory nor with roommates?

What is your annual household income? (If answered No to the above) / What is your annual income? (If answered Yes to the above) – Selected Choice

- $200,000+
- $100,001-$200,000
- $75,001-100,000
- $50,001-$75,000
- $35,001-$50,000
- $25,001-$35,000
- $15,001-$25,000
- $10,001-$15,000
- 0-$10,000
- Prefer not to answer

How many of the following does your household have? (If answered No to living in a college dormitory)

- Bicycles <text>
- Electric bicycles <text>
- Mopeds nor motorcycles <text>
- Passenger cars, vans, SUVs, pickup trucks <text>

How many of the following do you have? (If answered Yes to living in a college dormitory)

- Bicycles <text>
- Electric bicycles <text>
- Mopeds nor motorcycles <text>
- Passenger cars, vans, SUVs, pickup trucks <text>
- Motor homes, recreational vehicles, buses, nor large trucks <text>

What is your marital status?

- Single
- Married
- Divorced

Do you have children (under the age of 18)?
How many children do you have?
What is/are the age(s) of your child/children? - Child 1 - What is the age of your child?
What is/are the age(s) of your child/children? - Child 2 - What is the age of your child?
What is/are the age(s) of your child/children? - Child 3 - What is the age of your child?
What is/are the age(s) of your child/children? - Child 4 - What is the age of your child?
What is/are the age(s) of your child/children? - Child 5 - What is the age of your child?
What is/are the age(s) of your child/children? - Child 6 - What is the age of your child?
What is/are the age(s) of your child/children? - Child 7 - What is the age of your child?
What is/are the age(s) of your child/children? - Child 8 - What is the age of your child?
What is/are the age(s) of your child/children? - Child 9 - What is the age of your child?
What is/are the age(s) of your child/children? - Child 10 - What is the age of your child?
Please complete the following question for each child: - Does your child live with you? - Child 1
Please complete the following question for each child: - Does your child live with you? - Child 2
Please complete the following question for each child: - Does your child live with you? - Child 3
Please complete the following question for each child: - Does your child live with you? - Child 4
Please complete the following question for each child: - Does your child live with you? - Child 5

Please complete the following question for each child: - Does your child live with you? - Child 6
Please complete the following question for each child: - Does your child live with you? - Child 7
Please complete the following question for each child: - Does your child live with you? - Child 8
Please complete the following question for each child: - Does your child live with you? - Child 9
Please complete the following question for each child: - Does your child live with you? - Child 10

What is your gender? - Selected Choice Female Male Other: _______________
What is your age?
Would you describe yourself as... (Please check all that apply) - Selected Choice Asian/Pacific Islander White/Caucasian Hispanic/Latino Black/African American American Indian/Native American Other: _______________

* Highlighted questions were included in the analyses in this thesis

APPENDIX C – Post-experiment questionnaire (bicycle simulator VR test)

Please provide the participant number given to you in your experiment confirmation email:
Did you experience any motion sickness while using the bicycle simulator?
Did you need to stop the experiment due to motion sickness?

How aware were you of events occurring in the real world around you while performing the assigned tasks in the virtual environment?

- (1) Not at all aware
- (2)
- (3) Somewhat aware
- (4)
- (5) Very aware

How immersed were you in the virtual environment experience?

- (1) Not at all immersed
- (2)
- (3) Somewhat immersed
- (4)
- (5) Very immersed

Did the virtual environment feel appropriately to scale?

- (1) Not at all
- (2)
- (3) Somewhat to scale
- (4)
- (5) Yes, appropriately scaled

To what extent did your experiences in the virtual environment seem consistent with your real-world experiences as a bicyclist?

- (1) N/A I do not bike in the real world.
- (2)
- (3) Somewhat consistent
- (4)
- (5) Very consistent

The following questions ask how realistic various bicycle movements were in the simulator.

- Bicycle Speed
  - (1) Not realistic at all
  - (2)
  - (3) Moderately realistic
  - (4)
  - (5) Very realistic
- Bicycle Acceleration
  - (1) Not realistic at all
  - (2)
  - (3) Moderately realistic
  - (4)
  - (5) Very realistic
- Bicycle Braking
  - (1) Not realistic at all
  - (2)
  - (3) Moderately realistic
  - (4)
  - (5) Very realistic

Bicycle Steering
- (1) Not realistic at all
- (2)
- (3) Moderately realistic
- (4)
- (5) Very realistic

How distracting was the controller that you used to brake?
- (1) Very distracting
- (2)
- (3) Somewhat distracting
- (4)
- (5) Not distracting at all

How realistic was the vehicle traffic in the virtual environment?
- (1) Not realistic at all
- (2)
- (3) Moderately realistic
- (4)
- (5) Very realistic

Do you feel more or less compelled to observe the "rules of the road" while bicycling in the virtual environment compared to bicycling in real life?
- (1) Less compelled
- (2)
- (3) No change compared to real life
- (4)
- (5) More compelled

How realistic was your sense of risk in the virtual environment?
- (1) Not realistic at all
- (2)
- (3) Moderately realistic
- (4)
- (5) Very realistic

How safe did you feel using the different kinds of bike infrastructure?
- Biking in the bike lane
  - (1) Not safe at all
  - (2)
  - (3) Somewhat safe
  - (4)
  - (5) Very safe
- Biking in the protected bike lane with pylons
  - (1) Not safe at all
  - (2)
  - (3) Somewhat safe
  - (4)
  - (5) Very safe
- Biking in the road with no bike infrastructure
  - (1) Not safe at all
  - (2)
  - (3) Somewhat safe
  - (4)
  - (5) Very safe

How safe did you feel concerning the cars driving past you while you were... -

Biking in the bike lane
(1) Not safe at all
(2)
(3) Somewhat safe
(4)
(5) Very safe
Biking in the protected bike lane with pylons
(1) Not safe at all
(2)
(3) Somewhat safe
(4)
(5) Very safe
Biking in the road with no bike infrastructure
(1) Not safe at all
(2)
(3) Somewhat safe
(4)
(5) Very safe

The three bicycling environments you experienced are listed below. Please select the one in which you felt the LEAST SAFE and the one in which you felt the SAFEST.
SAFEST
Biking in the road with no bike infrastructure
Biking in the bike lane
Biking in the protected bike lane with pylons
LEAST SAFE
Biking in the road with no bike infrastructure
Biking in the bike lane
Biking in the protected bike lane with pylons

Do you have any additional comments about the bicycle simulator? (e.g. Do you think you behaved similarly as you would have in real life in the same environment? Why or why not? Are there any elements of the simulator you would like to provide more feedback on?)

* Highlighted questions were included in the analyses in this thesis

APPENDIX D - Pre-experiment questionnaire (pedestrian test)

Please provide the participant number given to you in your experiment confirmation email

How did you hear about this study? - Selected Choice
- Word of mouth
- Social media
- A flyer
- Other: _______________

In the past week, have you _______ (please check all that apply)
- Walked to a destination or walked for recreation/exercise?
- Driven or ridden in an automobile?
- Ridden a bike?
- Taken transit?

The following questions ask you about the amount of time you devote to different activities each day.
- On average, how many hours of physical activity do you have each day? - Hours + Minutes
- On average how many hours a day do you use a smartphone? - Hours + Minutes
- On average how many hours do you spend outdoors each day? - Hours + Minutes
- Approximately how much time did you spend walking last week? - Hours + Minutes

If you have a smartwatch that counts your steps, how many steps on average per day do you take? (put N/A if you don't wear one nor count steps with one)

Do you have any visual impairments? - Selected Choice
- Yes - please explain here: _______________
- No

Are you color blind?

What is your current employment status? - Selected Choice
- Employed full-time
- Unemployed
- Student
- Self-employed
- Working part time
- Retired
- Other: _______________

What is the highest educational degree you have earned? – Selected Choice
- Less than high school diploma
- High school/GED
- Bachelor's degree
- Some college (no degree)
- Graduate degree

What is your annual household income? – Selected Choice
- $200,000+
- $100,001-$200,000
- $75,001-100,000
- $50,001-$75,000
- $35,001-$50,000
- $25,001-$35,000
- $15,001-$25,000
- $10,001-$15,000
- 0-$10,000
- Prefer not to answer

How many of the following does your household have?

Bicycles <text>
Electric bicycles <text>
Mopeds nor motorcycles <text>
Passenger cars, vans, SUVs, pickup trucks <text>
Motor homes, recreational vehicles, buses, or large trucks <text>

What is your marital status?
Single
Married
Divorced

Do you have children (under the age of 18)?

How many children do you have?

What is/are the age(s) of your child/children? - Child 1 - What is the age of your child?
What is/are the age(s) of your child/children? - Child 2 - What is the age of your child?
What is/are the age(s) of your child/children? - Child 3 - What is the age of your child?
What is/are the age(s) of your child/children? - Child 4 - What is the age of your child?
What is/are the age(s) of your child/children? - Child 5 - What is the age of your child?
What is/are the age(s) of your child/children? - Child 6 - What is the age of your child?
What is/are the age(s) of your child/children? - Child 7 - What is the age of your child?
What is/are the age(s) of your child/children? - Child 8 - What is the age of your child?
What is/are the age(s) of your child/children? - Child 9 - What is the age of your child?
What is/are the age(s) of your child/children? - Child 10 - What is the age of your child?
What is/are the age(s) of your child/children? - Child 11 - What is the age of your child?
What is/are the age(s) of your child/children? - Child 12 - What is the age of your child?
What is/are the age(s) of your child/children? - Child 13 - What is the age of your child?
What is/are the age(s) of your child/children? - Child 14 - What is the age of your child?
What is/are the age(s) of your child/children? - Child 15 - What is the age of your child?

What is your gender? - Selected Choice
Female
Male
Other: _______________

What is your age?

Would you describe yourself as... (Please check all that apply) - Selected Choice
Asian/Pacific Islander
White/Caucasian
Hispanic/Latino
Black/African American
American Indian/Native American
Other: _______________

* Highlighted questions were included in the analyses in this thesis