CYCLIST STRESS AND BIOMETRIC SENSING IN NATURALISTIC CYCLING

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BIOMETRIC SENSING AND CYCLISTS' STRESS IN NATURALISTIC ENVIRONMENTS

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LIST OF SYMBOLS AND ABBREVIATIONS

BLOS	Bicycle Level of Service
ECG	Electrocardiogram
EEG	Electroencephalogram
GPS	Global Positioning System
GSR	Galvanic Skin Response
IMU	Inertial Measurement Unit
IRI	International Roughness Index
LiDAR	Light Detection and Ranging
LTS	Level of Traffic Stress
SLaB	Seeing Like a Bicycle

SUMMARY

Cycling is gaining traction in the United States as a mode of transportation due to its plethora of benefits. However, cycling still makes up a very low percentage of modal share. One major hurdle to increased cycling modal share is that people feel cycling is unsafe and stressful. Many studies have considered cyclists' stress, but these studies have not allowed participants to self-define their stressors during a cycling experience. This dissertation fills this gap by combining in-ride, open-ended surveys/interviews with naturalistic cycling methods. Cyclists wore eye tracking glasses and rode instrumented bicycles equipped with GPS and LiDAR to allow researchers to gain a deeper knowledge of their surroundings and reaction to them.

This dissertation uses different combinations of sensors and survey techniques to explore cyclists' stress and demonstrate the value of these methods. The first study focuses on in-ride surveys and instrumented bicycle data to explore the differences between an emerging (Atlanta, USA) and an established (Delft, Netherlands) cycling city. Thematic analysis was used to assess the themes in the interview responses. In addition, GPS and LiDAR were used to further explore findings around cyclists' speed and close-pass events. Although there were differences in stressors between the locations, the results suggested that no matter the context, cyclists prefer separated, well-maintained bicycle infrastructure.

The second study uses eye tracking and survey data from Delft to explore how gaze behavior varies with stress, complexity, and stated skill. The results suggest that complexity is better adjusted via non-visual tasks, but that stress may influence gaze range. The split between motor-tactical skills and safety motives in cyclists showed cyclists with

comparatively high safety motives had a wider gaze range. This was in unexpected based on driving literature suggesting that researchers cannot assume cyclists gaze behavior from studies on drivers' gaze behavior. No set of measures for eye tracking in cycling has yet been settled upon, but the measures used here showed great promise for future work.

The third study uses eye tracking and survey techniques to continue exploring the finding that pavement is a top stressor. Data were collected in Atlanta via an online survey and a separate field experiment. In the online survey data, potholes were the most important pavement characteristic to cyclists' comfort, followed by debris, wide cracks, and unevenness. The eye tracking data showed that unevenness drew the most gaze, followed by potholes and debris. The results have practical implications for the prioritization of cyclist-focused pavement maintenance.

Combined these studies demonstrate the value of combining survey techniques with sensing in naturalistic settings. Furthermore, the findings can be used in bicycle infrastructure design and maintenance for low-stress and safe cycling. Portions of this dissertation have already been published as:

1. Gadsby, A. and Watkins, K. Instrumented Bikes and their Use in Studies on Transportation Behaviour, Safety, and Maintenance, *Transport Reviews*, 2020. DOI: 10.1080/01441647.2020.1769227
2. Gadsby, A., Hagenzieker, M, and Watkins, K. An International Observation of the Causes of Cyclist Stress using Quasi-Naturalistic Cycling. *Journal of Transport Geography*, 2020. DOI: 10.1016/j.jtrangeo.2020.102932

CHAPTER 1. INTRODUCTION

This dissertation presents research on cyclists' stress and perceived safety. The unique methods combine surveys, instrumented bicycles, eye tracking, and naturalistic cycling. Each chapter will rely on at least two data streams and highlight the potential of these methods for understanding road user perceptions and behavior. The dissertation is based on research from a published literature review, one published paper, and two working papers.

1.1 Background

Cycling has a plethora of benefits for both the user and society at large. For the user, cycling increases physical activity and associated health markers and provides a low-cost, and if designed well, convenient form of transportation (*1*, *2*). On a societal level, higher levels of cycling can mean fewer cars on the road resulting in lower emissions and improved safety and public health.

Despite these benefits, the percentage of trips taken by bicycle in the United States is less than 1% (*3*). Some cities within the United States and around the world have successfully increased cycling modal share with some of the best increasing it above 30%. Bicycle modal share in most cities could be improved, but many potential cyclists feel stressed, unsafe, and uncomfortable cycling with the current state of the infrastructure (*3*–*5*).

To describe the types of people who could be converted to cyclists if bicycle infrastructure were built, Roger Geller developed the rider type scale which separates cyclists based on their comfort and confidence cycling. He developed the original classification system based on Portland, Oregon's experience improving cycling infrastructure (*6*). The four categories are: "strong and fearless", "enthused and confident", "interested, but concerned", and "no way, no how". The "strong and fearless" cyclists will ride under any roadway conditions and view the term "cyclist" as part of their identity. These are the 1% cycling in US cities now. "Enthused and confident" cyclists will share the road but prefer specific bicycle facilities. The "no way, no how" category includes people who would never bicycle, comprising about one-third of the population. The remaining category, "interested, but concerned", comprises most of the population (~60%). This category includes people who would like to bicycle but are uncomfortable cycling without separated facilities. Misra *(8)* argued for a fifth category that would fall between "enthused and confident" and "interested, but concerned". They called this category "comfortable, but cautious." It comprises people who are enthusiastic about biking but are concerned about their safety, thus falling in between the surrounding categories. These categories will be used to describe cyclists throughout the dissertation.

Many studies have been performed to understand what makes cyclists outside of the "strong, and fearless" category hesitant or uncomfortable cycling. For example, studies have shown time of day (*7*), separation from motor vehicles (*8*), dedicated bicycle infrastructure (*9–11*), and traffic volumes (*12*) are significant contributors to cyclists' stress. Studies about cyclists' stress have mostly been survey or interview-based. Such methods when used outside the context of cycling heavily depend on recall which diminishes with time (*13–15*). Other studies have combined quasi-naturalistic cycling methods with brief surveys to understand rider characteristics. Despite addressing the lack of the cycling experienced from pure survey or interview-based studies, these studies have not allowed participants to define their stressors; researchers assumed stressors based on participant surroundings and a stated stress level. This leaves a missing link in our understanding of cyclists' stress between experienced stress and the cyclists' perceived reason for that stress.

Therefore, there is a need for open-ended, in-ride surveys and eye tracking to assess cyclists' stress levels combined with real-time data streams sensing the environment around the cyclist. This dissertation attempts to address the gaps in knowledge of cyclists' stress with an innovative method that combines quasi-naturalistic cycling with eye tracking and intra-ride, open-ended surveys. The contributions of this dissertation come both from the methods used and new insights into cyclists' stress.

1.2 Objectives

The primary objective of this research is to improve understanding of cyclists' stress and how real-time data streams, especially eye tracking, combined with survey methods can support new findings into cyclists' stress, and in the future, road user behavior. The associated research questions are as follows:

1. When allowed to self-define stressors, what do cyclists identify as stressful? Does this vary between an emerging and an established cycling city?
2. How does gaze behavior vary with stress, complexity, and stated skill?
3. Which pavement conditions matter most to cyclists' perceived safety and comfort?
4. How does the gaze given to pavement conditions vary by condition type and infrastructure type?

5. Can the use of in-ride survey techniques in combination with instrumented bicycles improve understanding of cyclists' stress?

1.3 Research Approach

The research approach was designed to address the primary objective and research questions. Data collection occurred three times. The first two data collection protocols were designed to be comparable, but the third was adjusted to be more specific. Despite the differences, all three were similar in process. The data collection for each study is described in more detail in the following chapters, but a brief overview is provided here.

The first round of data collection had cyclists in Atlanta riding a bicycle equipped with a variety of sensors including speed (GPS), proximity (LiDAR), and air quality (PM2.5) sensors. An MS Thesis (*16*) covers the results for the air quality sensors. The cyclists chose among four routes around Atlanta, both to improve familiarity with the routes and to give a cross-section of Atlanta for the air quality sensors. Each route took approximately 30 minutes to cycle and had a variety of infrastructure from fully separated to mixed traffic cycling. We surveyed participants along the route to gain their stated stress levels, then interviewed them at the end to gather their reasoning for their stress levels. In addition to the interview, they filled out a survey that covered their transportation attitudes, habits, and demographic information. Participants also wore eye tracking glasses, but because of both hardware malfunction and data loss due to bright sunlight, the eye tracking data was not used in this dissertation. However, the use of eye trackers in this round served as a test of the eye trackers for future data collection efforts.

The second round of data collection was designed to be a comparison to the first. The process was the same, except the route was in Delft, the Netherlands. We adjusted the survey for cultural appropriateness and added a cycling skill inventory. We also adjusted the setup to reduce the hardware malfunction that resulted in eye tracking data loss in Atlanta, but the overall process was essentially the same.

The first analysis performed on the data combined the interview/survey responses with the instrumented bicycle data from Atlanta and Delft. I used thematic analysis to assess the interview responses, and the instrumented bicycle data from the LiDAR and GPS to support key findings. A description of the study and results can be found in CHAPTER 4.

The second analysis focused on the eye tracking data from Delft. This was an exploratory analysis of the measures of gaze behavior that could be associated with cyclists' stress, skill, and navigational complexity. The measures explored were selected based upon literature review. The results of the exploratory analysis are included in CHAPTER 5.

Based on findings from the previous studies that highlighted the importance of pavement condition, the third data collection plan focused on pavement condition was conceived with adjustments for Covid-19 related safety precautions. The cyclists did not ride the instrumented bicycle but did wear eye tracking glasses while cycling along an approximately 30-minute route covering separated bike lanes, painted bike lanes, and mixed traffic facilities. Participants filled out an online survey about their experience, adjusted to reflect the focus on pavement condition. In addition to the eye tracking component, an online survey was sent out to a larger population of Atlanta cyclists and analyzed as well.

The final analysis used data from the third data collection. Visual and statistical methods were used to analyze the online survey results. The results of the survey informed the pavement distresses to consider for the field experiment. The eye tracking data was then analyzed in frame-by-frame analysis for the selected pavement distresses and compared to the survey results. The practical implications of the findings are discussed and highlighted in CHAPTER 6.

These methods demonstrate the value in combining biometric sensing, instrumented bicycles, and naturalistic settings to understanding cyclists' stress and suggest benefits to future studies of road user behavior and perception. The results range from theoretical to highly practical. The methods open the door for further studies into road user behavior and interaction, especially vulnerable road users.

1.4 Organization of the Dissertation

This section provided the motivation and research questions for this dissertation. The following section reviews literature on stress measurement and the use of eye tracking. Next, CHAPTER 3 consists of a previously published literature review covers the use of instrumented bicycles in transportation.

The following three chapters come from published or working papers and combined answer research question five. CHAPTER 4, extracted from a published paper, uses survey analysis and the instrumented bicycles to answer question 1. Thematic analysis was used to understand the main causes of stress in both Delft, the Netherlands and Atlanta, USA. CHAPTER 5 uses survey results and eye tracking data from the Netherlands to explore research question 2. This chapter has been extracted from a paper under review. CHAPTER

6 uses eye tracking and survey data from Atlanta to answer questions 3 and 4. CHAPTER 7 summarizes the findings and puts forth the contributions, limitations, and future work for this dissertation.

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CHAPTER 2. LITERATURE REVIEW: STRESS MEASURES AND EYE TRACKING

2.1 Stress Measures

Stress is difficult to define. Selye initially defined stress as "the non-specific response of the body to any demand for change", indicating that it is a complex response comprising psychological, cognitive, and behavioral components (*1*). This is a very fluid definition and is context-dependent in practice. Furthermore, stress is a latent construct that cannot be directly measured. It can only be measured through correlating measures with self-reported stress ratings. This literature review will cover the ways people measure stress and how eye tracking, the chosen measurement device, has been used in transportation. Further literature review within each chapter will cover eye tracking in transportation relevant to that chapter.

Based on previous work, the most ideal measurement of stress is to measure stress hormones such as cortisol and catecholamine (*2*). However, this requires invasive techniques that could not be used to gather real-time measures of stress in a dynamic setting. The most common non-invasive real-time measures of stress are heart rate variation, breathing pattern, blood pressure, galvanic skin response, brain waves, various eye measures, or a combination of these. Nandita and Gedeon reviewed these measures and ranked heart rate variation as the best primary measure of stress (*2*). Heart rate variation can be measured using electrocardiogram (ECG) and has been shown to correlate very well with stress (*2*). Unfortunately, heart rates do not just vary from person to person, but also with physical exertion. Respiration and blood pressure suffer from the same problem, but have not correlated as closely with stress as heart rate (*2*).

Galvanic skin response measures the change in electrical conductance on the skin associated with increased moisture. It has shown good relations to stress and cognitive load (*2*). But the sensors are typically placed on fingers and sensitive to vibrations, which would be challenging for someone gripping the handles of a bicycle.

Another measure, electroencephalogram (EEG) is used to measure brain activity. It is effective temporally, but requires attaching sensors to the scalp (*2*), which is not feasible for a naturalistic cycling study.

Others have used various combinations of these. For example, Shi et al. (*3*) used heart rate, GSR, respiration, and temperature to develop a personalized stress detection algorithm using support vector machines. Within the world of transportation, driver stress was measured by Healey and Picard using a camera, GSR, heart rate, and skeletal muscle activity (using electromyography) (*4*). However, they also stated that this setup was cumbersome and not useful in realistic situations. Due to the challenges of the other methods, we focused on eye tracking, which can take measures also shown to be good indicators of stress (*2*).

2.2 Eye Tracking

Eye trackers record eye movements and pupil diameter. These can correlate with mental tasks and attention but cannot show whether someone processed what they looked at or noted something without looking at it. Eye trackers use infrared light to create a reflection in the cornea and find the center of the pupil (*5*). The relative location of the reflection and pupil changes when the eye rotates and the head remains still (*5*). Using this information, the location of visual focus can be determined and mapped onto a world view.

There are three primary types of eye movements: saccade, smooth pursuit, and fixation. Saccades are very rapid movements of the eye, during which vision is blurred and mostly suppressed (*5*). They move the eye from one point of focus to the next. Fixations are moments of stationary focus, typically lasting between 1/10 and ½ of a second (*5*). Finally, smooth pursuit of eye movement is when the eye is following a target. Because the point of focus will move relative to the cyclist, a fixation will typically appear as a smooth pursuit movement to the eye tracking processor. This type of movement is typically not tracked by eye tracking software. It often results in using frame-by-frame analysis methods where the start and end of a fixation is manually computed. But Vansteenkiste et al. (*6*) found that with head-mounted eye tracking fixation-based and frame-by-frame analysis were about equally effective.

There are a variety of eye tracking measures that are known correlates of stress such as mental workload and emotion. Pupil size has been associated with positive and negative affect (*7*) and mental workload (*8*). Illumination is a concern when measuring pupil size outside, although in lab settings it has been possible to separate illumination from pupil dilation due to mental workload or affect. However, Palinko et al. (*9*, *10*) were able to separate the change in pupil diameter caused by illumination and that caused by cognitive load. They did this using a video with different colored trucks and varying the mental workload through additional tasks. Xu et al. (*11*) also found that cognitive load could be separated from luminance changes by changing the luminance while the participant did math problems of different levels of difficulty. Both studies were performed in controlled laboratory settings and may be more challenging in a real-world environment.

For blink rate, there have been mixed results, likely associated with the confluence between visual workload and mental workload. When separated, it seems blink rate increases with increasing mental workload and decreases with increasing visual workload (*12*). Controlling for both would be challenging in a naturalistic experiment.

Fixations and fixation duration are the most commonly used in eye tracking. They're used in UX research (*5*) to see where people look in stores or packaging. In driving it's been shown that hazard perception and higher skill are associated with longer fixations (*13*). Fixations are used to create heat maps and have also been studied in terms of compactness of gaze (*14*). Overall, fixations and general gaze behavior are diverse measures better discussed in specific contexts. For this reason, focused eye tracking-related literature review are included in each chapter using eye tracking.

2.3 Eye Tracking in Transportation Research

Researchers have extensively used eye tracking in driving studies and to a lesser extent in bicycle and pedestrian studies. An exhaustive review of driving studies with eye tracking is beyond the scope of this review. However, a selection of papers has been included to illuminate the uses of eye trackers for research on drivers and what might apply to cycling. Further literature review is included in CHAPTER 4 and CHAPTER 5 to support the use of eye tracking in these studies. This section will cover each mode separately, starting with driving, then walking, then cycling.

2.3.1 Eye Tracking in Driving Research

Eye tracking in driving research has covered a variety of topics. This literature review will include mental workload, distraction, driver fatigue, skill, and familiarity. Researchers have shown the effectiveness of eye tracking measures for driving studies. Marquart et al. (*8*) performed a review of eye-related measures of drivers' mental workload. They primarily considered blink rate, pupillometry, and fixation duration. They found blink rate had confounding influences and pupillometry was challenging due to illumination, but that fixation duration could be usable. However, Palinko et al. (*9*, *10*) explored the effect of illumination on pupil diameter in driving simulators. They found that separation of the effects of cognitive load and illumination is possible but requires knowledge of the illuminance. Their task and setting were highly controlled, so the findings may not apply outside of a laboratory setting.

Cognitive load and distraction are important for safety in driving. One research team looking at cognitive load, Lee et al. (*15*), studied the effects of cognitive load and visual disruption on visual attention. They found that cognitive load impacts both exogenous ("caught their eye") attention and endogenous ("directed to observe") attention. Overall, they determined that the effects of cognitive load and visual disruption were additive in their tendency to increase the likelihood of drivers missing safety-critical events. Nunes and Recarte (*16*) considered another safety concern, distraction from hands-free phone conversations. They looked at the cognitive demands of hands-free-phone conversations measuring fixation duration and location and pupil size. They found that the more complex the task, the narrower the field of vision.

Eye tracking has also been used to detect safety in terms of lighting and driver fatigue. Hu et al. (*17*) developed a model comparing pupil diameter change, luminance, and speed when driving into tunnels. Their aim was to recommend tunnel lighting designs for driver comfort and safety. Horng et al. (*18*) and later Kumar and Patra (*19*) developed driver fatigue detection algorithms based on video-images and the drivers' eye behavior. These relied heavily on data of how open the eye was.

Eye tracking has also been used to look at skill and familiarity. Chapman et al. (*13*, *20*) compared the gaze behaviors of novice and experienced drivers in a driving simulator. They found novice drivers fixate for longer times than experienced drivers and experienced drivers fixate more frequently, but for shorter durations. They also developed an effective intervention to train novice drivers in visual scanning (*20*). Mourant and Rockwell (*14*) attempted to improve understanding of driver familiarity by mapping eye-movement patterns of drivers as they repeatedly drove routes. They found that as familiarity grew, the gaze became more compact and focused lower near the horizon and the lane marker. Additionally, they found that drivers use peripheral vision for monitoring and foveal vision for detailed observation as necessary. The authors used maps of gaze location compared to the lane markers to visualize the data. Based on the reviewed studies, gaze distribution, fixation frequency and duration, and pupil diameter are the most common measures of gaze behavior used in driving studies.

2.3.2 Eye Tracking in Pedestrian Research

Most research involving eye tracking with pedestrians has focused on navigation/locomotion and lighting/architecture, but some have been transportation-specific. The architecture work looks at lighting and interactions of pedestrians with their footpath (*21–23*). The navigation and locomotion work focuses primarily on way-finding (*24–27*).

Within transportation-focused studies, researchers started, when eye tracking was fairly new, by studying the pedestrian gaze to gain a general description of their gaze behaviors (*28*). Additionally, researchers have studied pedestrian crossing behavior with a focus on children and elderly (*29*, *30*). Recent studies have been preparing for autonomous vehicles. For example, Dey et al. used eye tracking to study how pedestrians perceive motor vehicles (*31*). They intended to use their findings to inform design for autonomous vehicles. These studies used fixations (duration and frequency) and gaze distribution to measure pedestrian gaze behavior.

2.3.3 Eye Tracking in Cycling Research

Although there is growing interest in using eye tracking for naturalistic cycling studies, publications are sparse. The most prolific author in this field is Vansteenkiste from Ghent University. He comes from a sports science background, so his studies have focused primarily on cyclist control of a bicycle (*6*, *32–35*). In addition to defining how cyclists maneuver their bicycle in a variety of situations, Vansteenkiste et al. (*32*) found that when biking on low quality roads cyclists tended to look close to them rather than at further off environmental hazards, which is relevant to studies of pavement condition on cyclist behavior.

Few studies have been published from a transportation engineering perspective. Ahlstrom et al. (*34*) from Sweden looked at the visual behavior of cyclists when using smartphones.

They found that, when required to perform the task, cyclists choose locations where they can spend longer looking at the phone and don't sacrifice safety necessary gazes to look at the phone. In terms of safety behavior, older cyclists are a concern. Igari et al. (*35*) from Japan researched where older adult cyclists look using a stationary bicycle and a video compared to young adults. They found the elder cyclists looked down at the pavement more than young cyclists who looked further ahead. Stelling-Konczak et al. (2018) studied glance behavior of teenage cyclists while using headphones. Although cyclists believe they compensate for the loss of audio signal by glancing more, it was found that there was no statistically significant difference in glance behavior when listening to music. Mantuano et al. (*36*) from Italy used eye-tracking to observe where cyclists look when mixed with pedestrians. They found that less experienced cyclists had a gaze pattern with more saccades and that cyclists tended to watch pedestrians more than physical risks or other cyclists. This suggested to the authors that participants considered pedestrian's movements less predictable than cyclists. None of these studies have looked at cyclist stress and there is still a lot of opportunity for further study in cycling using eye tracking.

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CHAPTER 3. INSTRUMENTED BIKES AND THEIR USE IN STUDIES ON TRANSPORTATION BEHAVIOUR, SAFETY, AND MAINTENANCE

This chapter has been adapted from: Gadsby, A. and Watkins, K. Instrumented Bikes and their Use in Studies on Transportation Behaviour, Safety, and Maintenance, *Transport Reviews*, 2020. DOI: 10.1080/01441647.2020.1769227

Abstract

Instrumented bikes are a critical tool to understanding cyclist behavior and preferences to incorporate cycling into modeling, designing, and planning the transportation system. Literature using instrumented bikes for transportation-related research has increased in popularity, especially in the last 6 years. As these studies are growing in number and maturity, now seems a good time to review how the bikes have been used, choices of sensors and methodology, and where there are gaps to be filled by future work. Therefore, the objectives of this literature review are to 1) discuss sensor choice in relation to methodology, 2) review findings from topics studied using instrumented bikes, and 3) discuss gaps in the literature. Two databases were searched for transportation-based literature using instrumented bikes with a total of 75 articles meeting the inclusion criteria. The literature was organized into nine focus areas with the most common topics being E-bikes, vehicles passing cyclists, and critical events. The results show that instrumented bikes are versatile tools that can shed light on a variety of aspects of cyclist behavior and safety as well as how to maintain the system for them. Various sensors were used for these studies, but cameras, GPS, and accelerometers were the most common. The review highlights the importance of study technique (naturalistic vs quasi-naturalistic vs other) on sensor choice with GPS and/or cameras being critical to any naturalistic study. However, GPS and cameras are the most challenging data types to work with due to difficulty and the time-consuming nature of processing the data. The variation in sensors also suggests some need to standardize set-ups for comparison of data across international contexts. Areas for future research are also discussed, including a new perspective for passing-distance studies and incorporating instrumented bikes into the connected vehicle/infrastructure space.

3.1 Introduction

Cycling has many well-known societal benefits including air pollution reduction, congestion alleviation, and improvement of public health (*1*). However, in most countries the number of cyclists is still low (*2*). There is increasing interest in capitalizing on these societal benefits by increasing bike modal share. In order to do this, people want to use cycling research to better understand how to incorporate cycling into models and make it more appealing in terms of both safety and comfort.

There are a variety of study methods used frequently in cycling research, including surveys, simulation, and naturalistic cycling. With portable logging devices becoming inexpensive to build with the advent of the Arduino and Raspberry Pi in the 2000s, bikes instrumented with sensors became increasingly usable for research in this field.

Since 2000, there have been many articles published, 75 in this review, that have used an instrumented bike. In that time, researchers have illuminated many topics around cycling, such as E-bike rider behavior and factors influencing passing distance. As these studies are growing in number and maturity, now seems a good time to review how the bikes have been used, choices of sensors and methodology, and where there are gaps to be filled by future work. Therefore, this article will 1) discuss sensor choice in relation to methodology, 2) review findings from topics studied using instrumented bikes, and 3) discuss gaps in the literature.

This article is organized such that the next sections discuss the method of the literature review, metadata of the research, and sensors used. Then, major findings in the literature in conjunction with sensors choices are reviewed with gaps in the research highlighted throughout. Finally, conclusions and directions for future research are offered.

3.2 Method

This section describes the methodology for conducting the literature review, including the selection of databases and inclusion and exclusion criteria.

3.2.1 Search Terms

Two key phrases were searched: "Instrumented (Bike or bicycle or cycling)" and "Naturalistic and (Cycling or bike or bicycle)." The focus of this literature review is the use of instrumented bikes for transportation research, therefore the first key phrase was a natural choice. However, it was clear that some important studies were missing with just that key phrase. To remedy this, "Naturalistic Cycling" was also reviewed, which recovered the noted studies. Naturalistic cycling is a methodology that allows participants to cycle as they would normally with some means of observing their behavior. The two most common methods of observing their behavior are through fixed-camera video recording and instrumented biking. When this method is highlighted, the tool used is often more implicit in the title and key words, sometimes being phrased as "a bike equipped with", so these articles were often not identified with the instrumented bike search term. Combined, the authors felt this provided a comprehensive selection of articles.

3.2.2 Inclusion and Exclusion Criteria

To be included in this literature review, studies needed to meet five criteria. First, only research published in English was included. Additionally, the research needed to be published in a peer-reviewed format. Third, a bike equipped with sensors had to be used as part of the data collection process. Studies that only put sensors on the riders' body (I.e. in a backpack) were excluded because it would broaden the focus of this literature review beyond the scope of a single article. Fourth, the research had to be transportation planning or engineering focused. This meant that studies with a primary focus on health separate from transportation (I.e. potential for instrumented bikes in rehabilitation for illness/injury, air quality measurements, etc.) or bike design (I.e. improving crank shafts for sports cyclists) were excluded. Additionally, route choice as a category was excluded as there is a large GPS-based literature on route choice that would warrant a separate article and was not effectively captured using the chosen search terms. The data collection techniques used for these studies would be similar to other naturalistic studies in their route identification, therefore excluding these studies is not a loss to the sensor discussion. Finally, studies had to include at least some cycling outside. This excluded purely lab-based or simulator studies.

3.2.3 Databases

Three scholarly databases were searched using these search terms. The first database was the Transportation Research International Documentation (TRID) (*3*). TRID is maintained by the US National Academies' Transportation Research Board and contains research covering all modes and transportation disciplines. It was chosen because of its transportation focus and all articles in TRID were reviewed.

The second database searched was Google Scholar. Google Scholar was selected in order to broaden the search. Articles are listed in order of relevance to the keyword. Due to the high number of hits for each search, a cutoff point was needed. The 500th article was chosen as the cutoff point because there were no longer relevant articles for at least 50 articles prior to the 500th one.

The review through each database was done sequentially with three steps for each database. First, the database was searched for the terms “Instrumented (Bike or bicycle or cycling).” Then a title search was conducted followed by abstract review. Then the process restarted with “Naturalistic and (Cycling or bike or bicycle)” as the key terms, removing any duplicates at the title search stage. In TRID for the instrumented bike key terms, there were initially 226 hits and for the naturalistic cycling 116 hits, with 35 articles meeting the inclusion criteria. Using google scholar the instrumented bike key terms had 1,210 hits and naturalistic cycling 5,160 although only 500 articles were considered for either, ultimately 44 articles met the inclusion criteria.

3.3 Metadata

This section will review metadata about the articles including publication year, journal, research location, and topic category.

3.3.1 By year

Figure 3-1 displays the number of publications by year. There were sprinklings of articles in the early 2000s. The earliest articles from 2003 and 2005 were out of New Zealand about instability riding over different line types.

From 2007, research using instrumented bikes became more regular, but still only 1-2 articles were published per year. The article in 2007 discusses passing of cyclists, the second most common topic of research reviewed. In 2012, the first article that discusses e-bikes as a focus, the most common focus in this review, appeared. From 2013, the research using instrumented bikes takes off with at least 9 articles per year since. In 2019, 5 articles had already been published by June, suggesting another year with a high volume of research using instrumented bikes. The increase in interest in the last 6 years suggests now is a good time to review what has been done, the methods used, troubles faced, and existing needs.

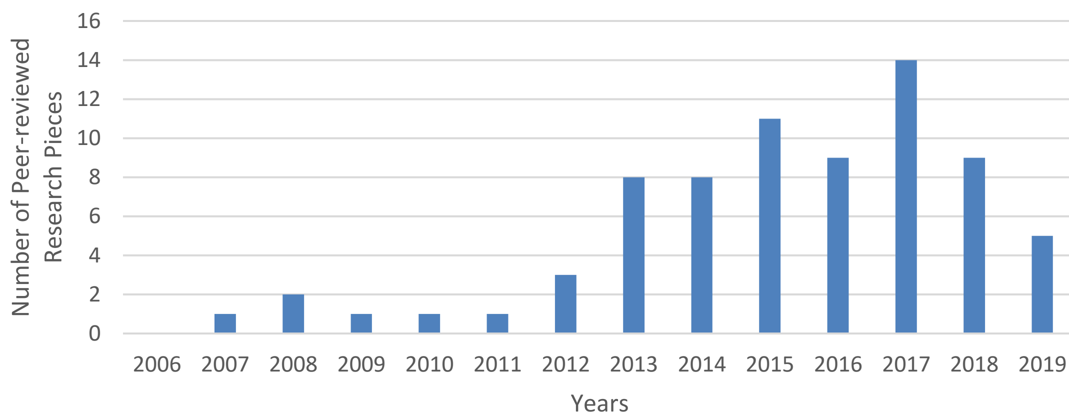

Figure 3-1 Number of peer-reviewed research pieces by year up to June 2019

3.3.2 By location

Figure 3-2 displays the number of publications by country. Looking at the research produced by country, the United States is leading. Considering the number of published research pieces by continent, Europe comes out on top with more than double the articles out of North America.

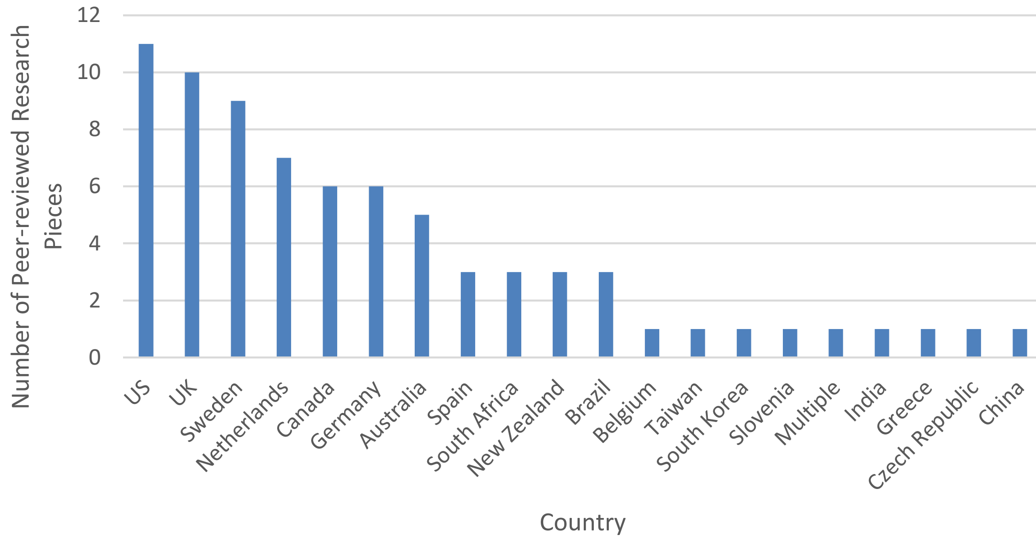

Figure 3-2 Number of peer-reviewed research pieces by country

3.3.3 By journal

The breakdown by journal is shown in Figure 3-3. The journal with the most publications on this topic is Accident Analysis and Prevention with 17 articles followed by Transportation Research Part F with 10 articles.

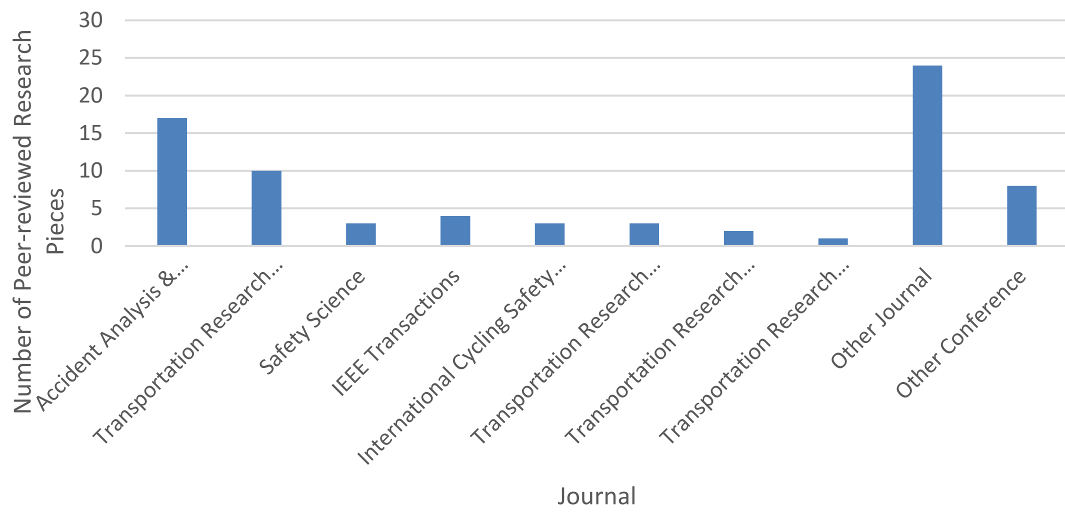

Figure 3-3 Number of peer-reviewed research pieces by journal

3.4 Sensors and Data Collection

A wide variety of sensors are used for research with instrumented bicycles. The choice of sensor to use is heavily dependent on the objective of the study. If all camera directions are counted as one type of sensor, most studies use three or fewer sensor types, with the most common number of sensor types being one. The most common sensors used were GPS and cameras, especially forward-facing, followed by accelerometers, gyroscopes, and speed sensors.

Table 3-1 below shows the types of sensors used, the number of studies each sensor was used for, and the topic categories of the articles. Note that some studies use an inertial measurement unit (IMU) which acts as an accelerometer, gyroscope, and sometimes magnetometer. For Table 3-1, use of this sensor has been included in accelerometer, gyroscope, and magnetometer.

Table 3-1 Sensors and their uses

Sensor	# Studies Using the Sensor	Focus Area of the Study
GPS	45	Age, Conflicts, E-Bikes, Infrastructure Management, Cyclist Stress, Human Control, Passing, Vehicle Detection
Forward Camera	37	Age, Conflicts, E-Bikes, Human Control, Infrastructure Management, Cyclist Stress, Passing
Accelerometer	34	Age, Conflicts, E-Bikes, Human Control Infrastructure Management, Cyclist Stress, Passing, Vehicle Detection
Gyroscope	22	Age, Conflicts, E-Bikes, Human Control, Passing, Vehicle Detection
Speed	20	Age, Conflicts, E-Bikes, Infrastructure, Passing
Lateral Distance	16	Conflicts, Infrastructure, Passing, Vehicle Detection
Magnetometer	14	Age, Conflicts, E-Bikes, Infrastructure, Passing
Side Camera	12	Conflicts, Infrastructure, Passing
Egocentric Camera	11	Age, Conflicts, E-bikes, Human Control
Rear Camera	9	Age, Conflicts, E-Bikes, Infrastructure, Passing
Pedal Sensors	6	E-Bikes, Infrastructure
Brake Sensor	6	Conflicts, E-Bikes, Infrastructure, Human Control
Steering	6	Age, E-Bikes, Human Control, Infrastructure
Pressure Sensor	3	Conflicts, E-Bikes
Current Sensor	2	E-Bikes
Handlebar Strain	2	Human Control
Sitting Force	2	Human Control
Other	7	Age, E-Bikes, Human Control, Infrastructure

The purpose of the study and the method (naturalistic vs non-naturalistic) define the best selection of sensors. For example, GPS or cameras (usually both) are needed for a naturalistic study as cyclists can ride anywhere, but these are not always necessary for a pre-specified route that a quasi- or non-naturalistic study would use.

However, there can be multiple ways of accomplishing the same task. For example, the studies looking at passing distances either used a sensor for lateral distance (ultrasonic was the most common, but LiDAR was used as well) or a camera. There are benefits and tradeoffs for each choice. Lateral distance sensors cannot tell the researcher about the type of vehicle, but the data can be faster to process. Video data can show the type of vehicle, but processing time can be very long. For example, Chuang, Hsu, Lai, Doong & Jeng (*4*) who studied passing distance noted that it took one person-day of work to record events and road facilities for a half hour of camera data.

Cameras and GPS, although the most popular sensors, were the most troublesome. As mentioned, cameras often required manual encoding which requires very long processing times noted by Chuang et al. (*4*), Huertas-Leyva, Dozza, and Baldanzini (*5*), Gustafsson and Archer (*6*), and Westerhuis and de Waard (*7*). GPS data can be challenging as it can be interrupted by tall buildings or other fixtures blocking the sensor, and the accuracy may not be high enough to determine exactly which road a cyclist used. It can be time consuming to clean the data, snap to maps, and process as was noted by Gustafsson and Archer (*6*), Gehlert et al. (*8*), Gorenflo, Golab and Keshav (9), and Mackenzie, Thompson and Dutschke (*10*) . These challenges of interruption and long processing times are important to consider when planning a project that requires video data and/or GPS.

Gorenflo et al. (*9*) wrote an article dedicated specifically to lessons learned around data collection, management, and analysis. Some lesson highlights include doing a full pilot project first and testing sensor types and sampling frequencies. They also recommend collecting redundant data in case of a sensor failure which happens frequently which was also noted by other researchers including Mackenzie et al. (*10*) and Gehlert et al. (*8*).

Another challenge is that there is a lack of standardization in the equipment and techniques used for these studies. Without some standardization, it can be challenging to compare studies because variation in technique, definitions, and data format can render studies non-comparable. Westerhuis and de Waard (*7*) note this need for standardization in their paper. Two authors looked into standardization options: Xie et al. (*11*) developed a vibration measurement system and Ambroz (*12*) considered the usefulness of raspberry pis for instrumented bikes. Two others published articles just on their data collection protocol, but no follow-up papers have been published yet (*13*, *14*). As this field evolves, it may be of interest to researchers to develop a standardized package of equipment and definitions so that studies from different contexts and transportation cultures can be meaningfully compared.

3.5 Major Findings by Topic

The major findings grouped by a general focus topic will be covered in this section with a discussion of the sensor-type decisions for each topic included. For tables showing information on the article and data collection strategy separated by section, visit Appendix C. Instrumented BIcycle Literature Review Table.

3.5.1 Studies Focused on the Influence of E-bikes on Cycling Behaviour and Safety

The E-bike studies attempt to assess the safety impacts of E-bikes as they become more popular around the world. Overall, the results are very consistent.

There is a strong consensus that people go faster when they ride E-bikes (*5*, *15–20*). Langford et al. (*20*), who studied E-bikeshare use in a university setting in Tennessee, found that E-bike riders rode on average 3.3 kph faster than conventional bike riders. Huertas-Leyva et al. (*5*) used naturalistic methods with six participants riding for two weeks each and found that E-bike riders travelled on average 22% faster than conventional bike riders. A study out of the Netherlands (*17*, *18*) found that the speed difference between E-bike and conventional bike riding was dependent on the complexity of the situation with cyclists riding only about 1.5 kph faster on E-bikes in complex situations and about 3.5 kph faster in simple situations. The German Naturalistic Cycling Study found that E-bike riders travelled on average 17.4 kph and conventional riders 15.3 kph (*15*, *16*). From these varied contexts, a range of speed increases of about 2-3.5 kph when riding E-bikes has been shown.

The majority of the studies that analyzed cyclist speed incorporated speedometer data, while only two studies (*5*, *20*) acquired speed data via GPS. Langford et al. utilized bikeshare bikes that feature GPS as standard equipment thus making the use of GPS for the collecting of speed data the natural choice. However, neither study specifically discussed the reasoning behind their sensor selection. Based on the drawbacks GPS can pose (i.e. inaccuracy without a clear view of the sky), studies that want to prioritize speed data may benefit from supplementing GPS data with data collected from a speedometer, as the other studies had done.

When looking at conflicts, there was consensus that E-bikes experienced more risk than conventional bikes, particularly at intersections. As part of the German Naturalistic Cycling Study, Petzoldt et al. (*15*) found that conventional bike riders' risk of a conflict did not significantly increase at intersections, however the risk of conflict for E-bikes doubled at intersections. In line with this finding, (*21*) found that E-bike riders conflicted more frequently with cars, especially heavy-duty vehicles, than conventional bike riders and hypothesized this was due to drivers misperceiving the cyclists' travel speed. Conflict-based studies require the use of a variety of sensors, typically including GPS and cameras, but also brake sensors as used in Huertas Leyva et al. These sensor choices will be discussed further in the conflicts section.

Outside of conflict-based analysis, two associated studies (*17*, *22*) measured the mental workload of their participants using a peripheral detection task. They found that cyclists adjusted their speed to keep mental workload consistent, but for older cyclists, their speed adjustment in complex situations was insufficient. E-bike riders may also feel less safe as they were more likely to wear a helmet in the German Naturalistic Cycling Study (*23*). However, looking purely at risky riding behavior, Langford et al. (*20*) in the United States and Schleinitz et al. (*24*) in Germany both found that E-bike riders' behavior is not different from conventional bike riders. Overall it appears that E-bike riders may behave approximately the same to conventional bike riders except the slight speed increase, but the slight speed increase may expose them to greater risk. The primary sensors used for these findings include participant-facing (aka egocentric) cameras and GPS.

Due to the motorization of E-bikes, the stability differs. Twisk et al. (*25*) had riders perform various tasks such as mounting, accelerating and braking, on both conventional and electric bikes. They found E-bikes were less stable in the early portion of the mounting process than conventional bikes. Kovacsova et al. (*19*) also studied the stability of cyclists on both bike types. They found that people rated their performance on accelerating and maintaining speed tasks better on an E-bike, but other tasks such as turning and braking better on conventional bikes. They also found that E-bike riders accelerate to speed more quickly than conventional bike riders. Both of these studies used accelerometer and gyroscope data to measure cyclist stability.

The reduced effort to accelerate and maintain speed on E-bikes suggests they could be used for longer trips. The WeBike Project in Canada sought to understand the usage of E-bikes by providing instrumented electric bicycles to 31 University of Waterloo-affiliated students and faculty (*9*, *26–28*). The participants rode the bikes naturalistically while the WeBike team collected data about their usage and charging habits. They found that the bikes were used mostly for commuting trips with over 70% of trips under 20 minutes (*27*). They found no evidence of range anxiety and that charging habits differed between the faculty and students with students taking two more trips between charges than faculty (*28*). They developed an algorithm to predict the remaining range (*26*). Lopez et al. (*29*) studied the usage of E-bikes using GPS and naturalistic methods in Belgium. They came to the conclusion that commutes up to 13 km are still viable for E-bike riders (*29*). One of the WeBike team's more interesting findings was that the participants' predicted usage and actual usage of the bike were not correlated, which they suggest means that people in general are uninformed about E-bikes which could be a barrier to adoption (*28*). Such large benefits will need to be communicated better to encourage usage of E-bikes for longer travel distances. These studies relied heavily upon GPS for the distance, location, and speed data as well as sensors that could tell the remaining charge in the battery.

Based on these findings, E-bikes have potential to allow for longer bike commutes, but also lead to higher speeds and higher conflict rates. Overall, these studies relied most heavily upon GPS, speedometer, camera, and charging data. The charging data would be unique to E-bikes, but the other three are candidates for widespread use in instrumented bike studies. There is a need for improved E-bike-specific sensing equipment for some studies. For example, the WeBike findings' main limitation in terms of charging was that they asked their participants to keep the bike charged because the smartphone collecting data used the same battery. They acknowledge that many charging events occurred with nearly full charge, which could be due to this request (*27*). Additionally, their range prediction model is a good start, but was limited by them not having information about assistance level and low frequency of GPS data (*26*). Most of the E-bike studies compared conventional bikes and E-bikes, so the sensors chosen were mostly applicable to both. However, there is space for E-bike specific research in the literature, for example studying charging habits or range prediction, that may require new types of instrumentation specific to the electrical components.

3.5.2 Studies Focused on Factors that Influence Motor Vehicle Overtaking Distance and Speed

Studies regarding vehicles passing cyclists most frequently use a lateral distance sensor such as ultrasonic or cameras to detect vehicle distances. Unlike the studies on E-bikes, the results are mixed, especially regarding the usefulness of bike lanes for increasing passing distance.

Four studies (*4*, *30–32*) found that bike lanes increased passing distance while 3 studies (*33–35*) found that bike lanes decreased passing distance, and another two claimed the effect was inconclusive (*36*) or not a significant variable (*37*). The sensor choices were varied in both cases. There could be many explanations for the mixed results including driver culture, lane width, cyclist positioning, and definition of lateral clearance. However, there is support for both sides from various contexts. It is likely to be what Stewart and McHale (*37*) and Shackel and Parkin (*36*) suggest, that the presence or absence of a bike lane is not the most important factor influencing the passing distance.

Two factors that have consistently come out of the research as important to passing distance were the ability of the passing vehicle to safely move into another lane and lane width. Stewart and McHale (*37*) developed a generalized linear model from 1,908 observations with 11 variables. They found cycle lane width to not be statistically significant. The top three most significant variables were the absolute road width, presence of on-street parking, and the presence of an opposing vehicle. In contrast, Beck et al. (*35*) found that most close passing events occurred without the presence of parked cars. Shackel and Parkin (*36*) also developed a linear model and found having 2 lanes in the same direction and greater lane widths were associated with greater passing speeds and distances. Love et al. (*31*) and Venter & Knoetze (*38*) both used linear regression and also found lane width to be a significant variable. Dozza, Schindler, Bianchi-Piccinini, & Karlsson (*39*) found that lane width didn't impact passing distance, but the presence of oncoming traffic reduced it. Mehta et al. (*40*) developed a model to estimate the number of unsafe passing events cyclists experience per hour. They also found that the probability of an unsafe passing event is much higher in restricted settings where the vehicle cannot change lanes. Vanderschuren and Ithana (*41, 42*) found that on high mobility roads (typically having more and wider lanes) the passing distances were larger. Overall, it seems when looking at passing distance, the focus should not be on the presence or absence of a bike lane, but on the ease with which a driver can give space to the cyclist. These studies utilized lateral distance sensors or cameras to detect close-passes and information about the infrastructure surrounding the cyclist to look at what influences passing distance. Although detecting a close pass is critical to these studies, the contextual information is also important. Cameras can be used to detect presence of traffic at the time of passing, although doing so can be processing intensive. Additional data, such as surveys of the infrastructure are needed to supplement the camera data.

In research that is only possible with the use of cameras able to capture information about larger vehicles, including buses and freight trucks, researchers found that these larger vehicles typically passed closer (*33*, *34*, *42*, *43*). This could be due to them having less space to maneuver within the lane (*42*) and that passing can take longer (*39*).

Overall, there is good support that passing distances are most greatly influenced by the space with which a vehicle can safely maneuver. Unfortunately, there is a tradeoff as wider driving lanes result in higher speeds. There is strong support for speed not influencing passing distance (*32*, *35*, *36*, *39*). These studies used a mix of video-based calculation (*36*, *39*) and speed limits (*32*, *35*) to determine driver speed. However, Llorca et al. (*44*), the only group using a vehicle speed specific sensor found that speed did influence cyclists' risk perception due to the aerodynamic forces caused by higher speeds, especially in combination with large vehicles. Bike lane width may be a way to reduce the driving lane width while still increasing space available to pass. However, there is evidence that vehicle drivers are less likely to change lanes or encroach on the next lane to pass a cyclist if there is an existing bike lane (*32*). Barring modal separation, the solution may be to include the 3-foot passing distance as a buffer to the bike lane.

Walker (*43*) considered how appearance influenced passing behavior by testing both helmet use and apparent gender. He found that when wearing a helmet, he was passed more closely, and when appearing female, he was given more space. Love et al. (*31*) and Chuang et al. (*4*) both also found that drivers give women more space when passing. As a follow-up to his first study, Walker et al. (*30*) explored a range of bicyclist outfits' impacts on passing behavior. He had outfits ranging from novice rider to sports cyclist and commuter. Despite his previous findings about helmets, he found that the outfit had no impact on driver behavior. Although women (or long-haired cyclists) may be given more space, no outfit appears to effectively influence driver behavior so efforts will need to come from elsewhere such as improved infrastructure.

Overall, two sensor types were used to measure vehicle passing distance: lateral distance and cameras. Lateral distance data is more specific and faster to process, but cameras are able to capture data including vehicle type and instantaneous traffic volumes. In addition to passing distance, passing speed was also measured in several studies. This was measured via three methods: the use of two separated lateral clearance sensors, cameras, and a speed laser for vehicle speeds. Measuring speed also requires knowing the cyclists' speed so GPS or speedometer, preferably one the cyclist can read to maintain a set speed, is also needed. Although the sensors used are critical to these studies, they use only a small number of sensors.

Unlike the other studies in which cyclists are always the focus, these studies center on observing driver behavior. They can be naturalistic or not for the cyclist, but they would always be naturalistic for the drivers. Because of this, the cyclist participants are often irrelevant. Due to low sensor and cyclist participant needs, this area would be one of the easier areas to develop a uniform data collection system and strategy. Based on the findings, this data collection system should include a way of measuring lateral distance and vehicle type. A robust data collection system would also consider what additional data is needed, such as lane widths and numbers. If choosing a naturalistic method allowing the cyclist to choose their route, the way of collecting this data will need to be on-board the bike but could be collected manually if routes are known. Vehicle speed did not seem to influence passing distance, but did influence the stress caused by them, so it may also be relevant to some studies. In that case, both vehicle and cyclist speed measures are needed.

3.5.3 Studies Focused on Infrastructure Management

The studies involving infrastructure can be separated into two focuses: specific features and maintenance. These studies rely heavily on accelerometer data.

Five studies looked at specific features. Two studies from a New Zealand group (*45*, *46*) looked at line types and road objects' influence on cycle stability. They measured stability using potentiometers for steering angle and accelerometers. Their overall finding was that instability was not simply a function of height. Of the 20 objects/line types they studied the worst were rough ground, round utility access cover, domes, and loose gravel. Vasudevan and Patel (*47*) studied the discomfort caused by speed humps for cyclists and motorized two-wheel vehicles using accelerometers at the handlebars and seat. They found that the discomfort was greater for cyclists, especially at the hands. A study out of Greece used GPS to look at the braking profile of cyclists in relation to pavement type. They found that asphalt provided the best friction among asphalt, concrete, and thermoplastic colored lanes (*48*). Lee et al. (*49*) attempted to determine the minimum one-way bike lane width using

GPS capable of real time kinematics. They found, based on essential maneuvering space, that 2 meters is the minimum width with no curb or gutter.

Six of the studies looked at measuring the pavement condition for maintenance purposes. Nuñez, Bisconsini, & Rodrigues da Silva (*50*) developed a method of evaluating the condition of cycling infrastructure using video recordings, GPS, and accelerometers. They found that pavement did influence vertical acceleration. Concrete had the least vibrations and paving bricks the most. Neto et al. (*51*) categorized surfaces using an accelerometer and GPS. Bil et al. (*52*) compared vertical acceleration readings with subjective comfort ratings of their participants. They found that there was a strong correlation (coefficient of –0.94) between the subjective rating and the accelerometer readings converted into Dynamic Comfort Index values. They also found that the speed of the cyclist impacted the accelerometer results which was not controlled for in any other study. A group from the UK (*53*, *54*) developed a bike for assessing pavement condition which they call IntelliBike. Their bike is equipped with forward and downward cameras, an accelerometer, GPS, speedometer, sound meter, light meter, and microphone. They found that the most important factors in comfort were surface maintenance related ones such as debris and defects. None of these studies tied their values to already-existing pavement evaluation systems.

Li et al. (*55*) began filling this gap by measuring pavement texture using existing methods for vehicle comfort ratings and comparing those results, on-bike accelerometer, and subjective ratings to describe the correlation between pavement management treatments and rider experience. This study was a step in the direction of tying maintenance for cyclists into existing maintenance practices, but the focus on sport cyclists on rural and suburban roads is a limitation to expanding the method to urban spaces where most commute cycling occurs.

These studies primarily used accelerometer and GPS. However, this combination may be too simplistic to acquire data about the range of riding surface characteristics that can affect cyclists including friction, debris, and potholes. IntelliBike is a more complex data tool for pavement data. Accelerometer and GPS are very versatile, however many of the sensors added to IntelliBike are not used in many other types of studies, so which sensors to choose would be dependent on the desired versatility of the system and which pavement conditions the study is trying to capture.

3.5.4 Studies Focused on Cyclist Stress

Not just physical comfort, but also emotional comfort is important to a cyclist's decision to ride. With 51 participants from their university, Feizi et al. (*56*) used an instrumented bike equipped with sensors including forward-facing camera, GPS, steering sensors, and rider body position sensors along with a comfort survey to understand cyclist comfort. They found that cyclists with self-reported lower skill levels resulted in a higher probability of a low comfort rating. They also found that the more intersections and times a cyclist must turn or maneuver, the lower the comfort rating. Yamanaka, Xiaodong, and Sanada (*57*) developed evaluation models incorporating cyclist stress. They collected data including camera, lateral distance, and braking data in China, France, and Japan to build their model which they conclude works.

Caviedes and Figliozzi (*58*) used skin conductivity as a stress measure to study the impact of traffic conditions and infrastructure type on cyclists' stress levels. Their bikes were equipped with GPS, powermeters, and two helmet cameras. They also found that peak hour stress was higher (17%) than off-peak hours and that the most stressful events occurred around intersections. Along segments the most stressful events involved other travelers (vehicles or pedestrians) entering the bike lane. However, their study only had 5 participants. Similarly, Nunez, Teixeira, et al. (*59*) analyzed the relationship of stress with noise, vertical acceleration, presence of cycle paths, and period of day using the same camera/accelerometer set up from their infrastructure-focused study. They used a smart band measuring skin conductivity, correlated with stress. They were able to map this stress data and compare it to their instrumented bike data. Their methods and participants are not well described besides having a small sample size, but their simple choice of cameras and accelerometers combined with a measure of stress seems to be a viable option for measuring cyclist stress.

There is still much room for further study to develop a body of knowledge surrounding the causes of cyclist stress in real environments. A variety of sensors were chosen for the studies including sensors to observe the surroundings (i.e. cameras, lateral distance sensors), the cyclists' movements (i.e. GPS, steering, powermeters), and the cyclist themselves (i.e. galvanic skin response). Two small studies were able to primarily rely on cameras and accelerometers on the bikes, but perhaps the difficulty of extracting all the necessary data from videos led to the small sample sizes of the data presented in the resulting papers. The causes of stress and comfort can be varied, perhaps even varying by location, and the sensors needed to study it are likewise varied and defined by what the researchers want to explore as a cause of stress. In order to create a consistent measurement unit, a consistent set of potential stressors must be defined first, making this one of the more complicated topics to design a measurement method for.

3.5.5 Studies Focused on Conflicts and their Causes

Naturalistic cycling is the most popular way of using instrumented bikes to study conflicts. The most common definition of a critical event is taken from naturalistic driving studies - whenever a party must slow down or change directions in response to an event. Because of this definition, most studies incorporate cameras, GPS, and some means of measuring the cyclists' braking activity.

There is a consensus that intersections, crossings, and poorly maintained infrastructure are the locations with the most conflicts. Dozza and Werneke had 16 riders riding for 2 weeks each on bikes equipped with a forward camera, IMU, GPS, and brake sensors (*60*). They found that attributable risk was highest for intersections, followed by pedestrians/bikers and the pavement surface. Additionally, they found that risk of critical events was higher in proximity to intersections and when the road surface was poorly maintained. They delved deeper into this data and combined it with interviews with the participants (*61*). They found that visual occlusion was common around events both at intersections and with other bikes. The German Naturalistic Cycling Study also considered critical events using cameras, GPS, and speed sensors (*15*, *62*). They had 28 participants who rode for four weeks and found that most riders experienced only 1-3 conflicts. Critical events with vehicles were most frequently caused by motorists failing to yield. They also found that the risk of a critical event was 2 times higher on bike infrastructure than on-road, accounting for distance travelled on each (*15*). They did not single-out intersections, but did consider the conflict partners with over half (57%) of conflicts occurring with a bike or pedestrian (*62*), which could explain the finding that the risk of a critical event was higher on bike infrastructure .

Jahangiri, Elhenawy, Rakha, and Dingus (*63*) were concerned about cyclists' safety behavior and studied cyclist violations at signal-controlled intersections using bikes equipped with forward and egocentric cameras, GPS, accelerometer, gyroscope, and speed sensors. They found that cyclists were more likely to violate a red light when making right turns, and the risk of running the red decreases when cyclists have traffic to the side or in front of them. Schleinitz et al. (*24*) also used their data to look at cyclists running red lights and found a 20% violation rate. They also found that cyclists were most likely to run a red light when turning right, and that cyclists would frequently ride on the sidewalk to avoid a red. Overall, they found that cyclists are opportunistic and are more likely to run a red when there is good sight distance. The opportunistic cyclist view fits with the findings of both Jahangiri et al. (*63*) and Schleinitz et al. (*24*) findings regarding when cyclists run red lights.

Further supporting the opportunistic cyclist, Kircher et al. (*64*) studied cyclists' speed adaptation when performing self-paced smartphone tasks using forward and egocentric cameras on the bike and eye tracking and GPS on the cyclist. They found that cyclists adapted their speed and riding strategy to the conditions, thus generally choosing safe locations to perform the smartphone tasks.

A Spanish group decided to study conflicts specifically on two-way cycle tracks using cameras, GPS, a speed sensor and range finder on the bike. They found that pedestrians were the most common second unit, and crossings were the most common conflict and perceived as the riskiest (*65*). They also studied the meeting maneuvers between cyclists on two-way cycle tracks (*66*). They found that when there are obstacles beside the cycle track, cyclists ride closer to the center with a larger effect from obstacles at handlebar height than wheel height. On cycle tracks less than 1.6m wide, the frequency and intensity of the interactions increased with braking only being a significant interaction on these tracks.

Lawrence et al. (*67*) studied the risk of car door collisions in Australia using a bike equipped with cameras and GPS. They found that their sample encountered 55 cars/km and 2.3 opened door events per hour. People gave way to the cyclists 6.9 times per hour. They conclude that although people give way many more times than not, there is still challenge in addressing the risk of dooring for cyclists.

Gustafsson and Archer (*6*) conducted a unique study looking at commuter cyclists in Stockholm to understand accessibility and safety problems. They used GPS and a forward-facing camera on their instrumented bikes. They found the average speed to be 20.4 km/h with delay making up 13% of travel time. In cities, the average speed dropped to 16 km/h with delay making up 22% of the travel time. They identified 506 problems, 43% of which were attributed to safety problems and 56% to access problems. The safety problems were most frequently attributed to the design with the second most common being the road surface. Their work represents a unique perspective and method of studying bike accessibility, especially with the inclusion of delay that would be interesting to replicate in other cities.

The sensor choices are largely similar in these studies (cameras, GPS, speedometer and/or braking sensors), but the findings seem to vary related to the context (i.e. bikes in fully separated facilities, whether they are exposed more to motor vehicles or pedestrians). This topic of study would be benefitted by adopting the same definition of conflict. Therefore, these studies would benefit from a set of sensors geared to detect conflict, such as speed and/or braking sensors which are already typically used and IMU for sudden direction change. Furthermore, these are typically naturalistic studies that go for a longer period of time, so the sensor kit should be minimally invasive and easily powered to make it the most naturalistic.

3.5.6 Studies Focused on Human Control of a Bicycle

Instrumented bikes have also been used to study human control of bicycles. Cain and Perkins used steering, speed, acceleration, and angular velocity sensors to develop a model of cyclist steady state turning (*68*). Zhang et al. (*69*) also equipped the rider with an IMU to develop a rider pose estimation model.

Kooijman, Schwab, and Moore (*70*) used an egocentric camera, steering, frame lean and yaw rate, speed, and pedaling cadence sensors to identify the major human control actions involved in stabilization during normal biking. They found that very little upper body lean and only minor steering movements are involved. At low speeds, they found cyclists use their knees to stabilize the bike, but otherwise it is all done with steering. Twisk et al. (*25*) studied mounting behavior using a variety of sensors including a speedometer, gyroscope, and steering sensors looking at comparisons between older and middle-aged people and between conventional and electric bikes. They found that the most stable way of starting was while seated using the pedal to push off. Ma and Luo (*71*) used an instrumented bike with GPS and altitude sensors to develop models for acceleration behavior to be used in simulations. They found that gender and agility had significant effects on the acceleration behavior. Dozza and Fernandez (*72*) tested an instrumented bike with IMU, braking sensors, forward camera, and GPS to analyze bicycle dynamics in a naturalistic way. They found that they were able to describe maneuvers such as circumnavigating a car that had cut in front of a cyclist.

Overall, the sensors needed to measure cyclist dynamics are more diverse than in the other topics. Based on the sensor choices for these studies, IMU/gyroscope and steering sensors are the most critical in this field.

3.5.7 Studies focused on the Influence of Age on Cycling Behavior

Both older persons and children have been studied using instrumented bikes. As noted in the E-bike section, there have been a few articles comparing middle-aged riders to older riders (*17–19*, *25*) in relation to E-bike and conventional bike use. Kovacsova et al. (*19*) tested 61 participants within the age groups of 30-39 and 65-79 on both conventional bikes and pedelecs. They used speed sensors and accelerometers to find that older cyclists both accelerate and cycle on an E-bike at about the same speed as a middle-aged person on a conventional bike. This suggests that older cyclists use the E-bike to compensate for any loss of physical fitness. Kovacsova et al. (*19*) had the cyclists perform a series of tasks including a head check, braking, and low-speed cycling. The older cyclists struggled more with the head turn tasks and maintained balance by additional steer and roll motions. To detect these stability concerns they used steering sensors and accelerometer/gyroscope.

The articles by Twisk et al. (*17*, *25*) and Valkveld et al. (*18*) used the same dataset of 58 participants, half age 30-45 and the other half age 65 or older riding instrumented bikes equipped with a steering sensor, speedometer, GPS, IMU, and cameras. They also tested a series of tasks including mounting/dismounting, emergency braking, and low-speed riding. Additionally, they used a peripheral detection task to test mental workload. They found that the bike did not influence the mental workload as cyclists adapted their speed to keep this constant, but older cyclists had a higher mental workload than the middle-aged cyclists. The cyclists speed patterns were similar, but with the middle-aged cyclists consistently riding approximately 2.6 kph faster (*18*). Twisk et al. (*25*) looked specifically at mounting and found that muscle strength, which is correlated with age, influences stability with weaker cyclists having lower stability. E-bikes allow people to cycle into an older age, and as Gehlert et al. (*8*) discovered, it is easier to find older people who ride an e-bike. As E-bikes become more popular, there is increasing need for research on the safety and behavior of older cyclists.

These studies required the human control/stability sensors from previous sections and speed sensors to study the interaction of age, bike type, and speed/stability.

Studies involving children cycling on instrumented bikes are still uncommon. There was one study out of Australia by Hatfield et al. (*73*) that looked at the effectiveness of a cycling education program using naturalistic cycling with forward and egocentric cameras. They emphasize the benefits of their methodology, but, found no evidence that the program influenced behavior. Overall, it seems instrumented bikes have potential for studying children's behavior, but the tool needs to be applied in more contexts.

3.5.8 Studies focused on Vehicle Detection

With vehicles becoming more connected and autonomous, both how vehicles will detect vulnerable road users and how those users might detect vehicles is increasingly of interest. Three papers looking at this have been published in the last two years. A group in England (*74*, *75*) developed an effective bicycle positioning algorithm from cyclist kinematics including data from accelerometer/gyroscope and GPS to incorporate into the connected vehicle space. In Minnesota, a group is developing a laser tracking system to detect approaching rear vehicles (*76*). Their publication discussed the development of their algorithms and their preliminary field tests. Their system has shown potential.

None of these studies are bringing cyclists into the connected vehicle space, a frontier with potential for study using instrumented bikes. Instrumentation could be included that allows the bike to inform nearby road users and infrastructure of their location and speed to help improve safety and traffic flow. This could be especially useful on E-bikes which already have an on-board power supply, are opening cycling to a broader range of people, and are exposed to more risk. There is room for imagination and innovation here with how cyclists could be incorporated into a space with connected vehicles and infrastructure.

3.6 Conclusions and Future Research

This study compiled a literature review of topics studied using instrumented bikes. Research using instrumented bikes has increased rapidly in the last decade touching a variety of topic areas. The variety of research objectives covered shows that instrumented bikes are a useful, effective, and critical tool in cycling research. The most commonly used and most versatile sensors are GPS, cameras, accelerometers, and speedometers. A few key areas for future research are highlighted here.

Behavior of both cyclists and drivers interacting with cyclists can be subject to a large amount of regional variation, therefore it is of interest to compare results from different regions. However, there is need for consistency in definitions of key variables, such as critical event, across studies. Similarly, there is a desire for consistency in instrumentation. Although sensor choice is heavily dependent on the study goals, development of a sensor kit with some of the most common sensor types or designed for studies of a certain topic that could be built and used by many research teams would benefit the field. Each of the focus areas discussed above also included discussion of the most common and relevant sensors to the topic and could be used as a starting point for such a kit.

One area that needed more innovation in sensors was studies on E-bikes. Most studies have focused on the important comparison between conventional bikes and E-bikes, but this has led to studies using sensors that also work on conventional bikes leaving a gap in studies looking at E-bikes and E-bike riders themselves. This information would be valuable for use in planning for and advertising for E-bikes by governments interested in increasing bike modal-share where E-bikes may suit large portions of the population better than conventional bikes. Studies looking to study this side of E-bikes may require different sensors than the most common ones from previous studies. For example, speed sensors become less important but sensors detecting battery charge may become more important.

One of the biggest research gaps in terms of what instrumented bikes are being used for is the incorporation of bicycles into the connected vehicle space. Although some studies have begun looking at how vehicles can sense the presence of a cyclist, there are still no studies that use anything attached to the bike to communicate with other road users. With vehicles becoming increasingly connected, this is a time-pressing and critical research gap.

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CHAPTER 4. AN INTERNATIONAL COMPARISON OF THE SELF-REPORTED CAUSES OF CYCLIST STRESS USING QUASI-NATURALISTIC CYCLING

This chapter has been adapted from: Gadsby, A., Hagenzieker, M, and Watkins, K. An International Observation of the Causes of Cyclist Stress using Quasi-Naturalistic Cycling. *Journal of Transport Geography*, 2020. DOI: 10.1016/j.jtrangeo.2020.102932

Abstract

This study explores the influences of attitudes and setting on cyclists' stated causes of stress using survey techniques and quasi-naturalistic cycling in both Delft, The Netherlands and Atlanta, Georgia, USA. The study recruited 28 participants in Delft and 41 in Atlanta. Participants cycled approximately 30 minutes on specified routes in both cities on an instrumented bicycle. Prior to cycling, the participants filled in a written survey about their cycling habits, attitudes, and demographics. At specified points during and after the ride, participants were interviewed about their stress levels throughout the ride and the causes of those stress levels. Thematic analysis and statistical methods are used to understand the interactions of setting (country), attitudes, stated stress, and sensor data. The top three stressors were motor vehicles, pavement, and poor infrastructure; 83% of participants mentioned a motor vehicle causing stress, 64% mentioned road surface, and 58% mentioned infrastructure. The results confirm the importance of motor vehicle interaction to cyclist stress, but also highlight some new insights on stress such as the importance of pavement condition. Speed differentials between cyclists and vehicles were also shown to be important and suggested cyclists in Delft felt comfortable to travel their ideal speed. This speed preference was supported by GPS data that showed the cyclists in Delft were cycling at speeds about half (12 kph) that of the cyclists in Atlanta (24 kph). Review of close-pass events demonstrated that cyclists in Delft were more comfortable with closer passes which could be associated with their belief that motorists notice them and/or speed differences between the vehicle and bicycle. The results also suggest that number of vehicle travel lanes can have mixed impacts on cyclist stress. These findings can be taken into consideration when designing bicycle facilities to create low-stress cycling networks.

4.1 Introduction

Designing a low-stress cycling network is critical to encouraging cycling. There have been many studies on the causes of cyclist stress and stress/comfort-based rating systems, but there is still room for improvement in our understanding of cyclist stress. This study uses a new combination of quasi-naturalistic cycling, instrumented bicycles, and near real-time interviews to add to the existing body of knowledge on the causes of cyclist stress.

One major component of the existing literature on cyclist stress is stress/comfort-based rating systems for projects and road segments. The most widely known are Bicycle Level of Service (BLOS), Bicycle Compatibility Index (BCI) and Level of Traffic Stress (LTS). The designers of BLOS used cyclists' comfort ratings on roads with a variety of characteristics to develop their rating system. Significant variables include traffic volumes, number of through lanes, lane width, speed limit, volume of heavy vehicles, and road surface condition, among others (*1*). BCI was a parallel effort that used video clips to identify roadway characteristics' compatibility with cycling. BCI includes bicycle facility presence, width, vehicular volumes, speed, and presence of parking (*2*). Both BLOS and BCI require intensive data collection and complicated equations that do not easily show the relationships between each component and the result. This makes them challenging to calculate network wide. LTS (*3*) was an attempt to make a rating system that was more user-oriented and applicable across a network. The designers based the classification levels on a system similar to Geller's four types of cyclists (*4*), and the distinction between categories are based on Dutch design practice rather than through experiment (*5*). LTS variables include bicycle facility presence and width, parking presence, speed limit, bicycle lane blockage, and number of lanes (*3*). These rating systems suggest that road lane width, presence of parking, vehicle speeds, vehicle volumes, number of vehicle lanes, and bicycle facility presence are important factors in cyclist stress. However, these scales were developed based on post-ride video review, surveys about comfort, and assumptions from the literature, rather than data collected on real-time stressors identified by participants.

Additional studies have further explored causes of cyclist stress. These studies have found that time of day (*6*), separation from motor vehicles (*7*), dedicated bicycle infrastructure (*8–10*), and traffic volumes (*11*) are important influences on cyclist stress. Studies on cyclist stress are often exclusively survey or interview-based (*2*, *8–10*). By choosing to conduct interviews and surveys outside of the cycling experience, studies become dependent on recall which diminishes with time, can require prompting, and may be less specific than surveying in real-time (*12–14*). Although there is some evidence that surveys in combination with a video can provide similar results for comfort and safety ratings as an in-person experience (*15*), there is not yet evidence that cyclists would identify the same stressors without the additional cues an in-person riding experience offers.

Some studies combine quasi-naturalistic cycling methods with a rider characteristics focused survey, including demographics and transportation attitudes (*6*, *7*, *11*, *16*, *17*). Naturalistic cycling studies allow participants to cycle as they normally would without any set routes. Quasi-naturalistic studies put some limitations on naturalistic cycling, typically in the form of a specified route (*18*). Both Yamanaka et al. (*19*), who developed a bicycle to measure BLOS, and the developers of the BLOS (*1*) did couple quasi-naturalistic cycling with short surveys identifying the participants' stress levels during the ride. However, the participants themselves did not get to define the stressors, only their level of stress. By using quasi-naturalistic cycling methods without an interview portion to inquire why the cyclist was stressed, the defining of stressors is left to the researchers. Both interviews/surveys outside of a cycling experience and stress ratings mid-ride without a participant explanation for that rating result in top-down definitions of stressors. This results in stressors defined by the assumptions of the survey designers or data analyzers, limiting the scope of potential stressors.

Therefore, this study explores what may happen if the cyclist is able to define their own stressors through the combination of quasi-naturalistic cycling with near real-time interviews to find the gaps in researchers' assumptions of what causes cyclists' stress. To broaden the study, data were collected in both Atlanta, Georgia, USA and Delft, The Netherlands to gain perspective on stressors in what is often considered traditionally high- and low-stress environments for cyclists. Through this unique study methodology that allows for cyclists themselves to define their stressors, this international comparison aims to explore what cyclists find stressful to fill methodological gaps in the literature. Ultimately, the findings can inform design choices for low-stress bicycle facilities.

4.2 **Method**

The experiment that is the subject of this paper consisted of each participant cycling 25-30 minutes along a specified route. The participants rode an instrumented bicycle equipped with a variety of sensors including GPS, LiDAR, and cameras and filled out a survey about their stress levels, attitudes about transportation, characteristics as a cyclist, and demographic information. The following section provides greater detail about the methods used in the study.

4.2.1 *Locations*

The experiment was conducted in Atlanta, Georgia in the United States and Delft, Zuid-Holland in the Netherlands. The city of Atlanta has a population of approximately 500,000 people with approximately 6 million people in the metro area. As of 2016, Atlanta had a bicycle modal share of 1.4% (*20*). Delft is a smaller city in the Netherlands with a population of approximately 100,000 people. The Netherlands has a national bicycle modal share of just over 25% (*21*). In urbanised areas in the Netherlands, such as Delft, bicycle modal shares of almost 40% for trips between 1 and 7 kilometres are common (*22*). The Dutch have been improving their cycling network since a reversal from car-oriented policies in the 1970's (*23*). In contrast, Atlanta began to emphasize bicycles as a mode of travel with the conception of the multimodal circulator trail, the Beltline, in 2012, and has steadily increased the bicycle network since (*24*). Atlanta was assumed to represent a high stress cycling environment and Delft a low stress cycling environment based on their cycling traditions. These two cities were selected due to the home base of the universities in each location as part of a larger study on the influence of cyclist stress on behaviour. The contrast is expected to highlight the similarities in cyclist stress across environments. To keep some consistency in the environment for participants, the study routes within the cities were designed based on the same guidelines.

4.2.2 Study Route Design

The study routes were designed to cover a variety of infrastructure and land uses, as could be reasonably found within each city. All routes were circuitous and designed to minimize left turning movements. Four routes were chosen around Atlanta to encourage participation and allow participants to choose a familiar route, however the small city of Delft required only one route. Additionally, the data collection plan in Atlanta was also designed to have the coverage to support a study on air quality which was unnecessary for the Delft data collection plan.

The Atlanta routes were designed first, then the Delft route was designed to approximate the Atlanta routes. To create the Atlanta routes, maps of where people ride were made. These were made using Ride Report data from 2018, Relay Bikeshare data from 2018, and Strava data from 2014. These maps are provided in Figure 4-1. The most travelled roads are shown in red and have volumes over two standard deviations higher than the average road bicycled in Atlanta. The Ride Report data best represents commuters. The Relay Bikeshare data has many casual recreational riders, which can be seen by the dark red that covers the Beltline and Piedmont Park. The Strava data has a larger number of sports cyclists which caused some areas that would not be considered a road that a typical commuter might travel to have a high ridership. Areas with the highest volumes of riders were chosen as areas of focus for designing the routes. By combining the three sources, weighting the commuter-heavy Ride Report data the most, the cycling hot spots in the city were found.

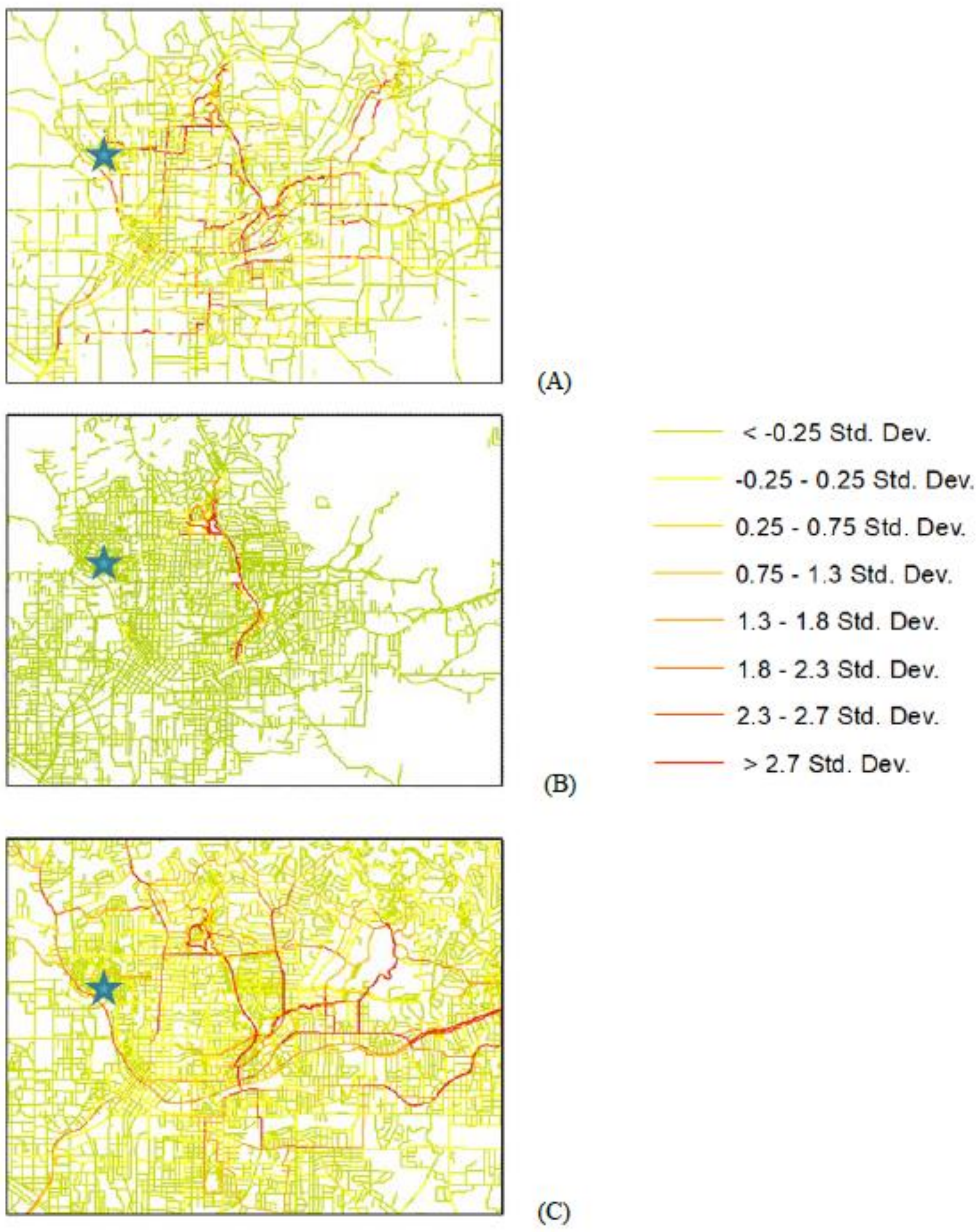

Figure 4-1 Maps used for finding biking hot spots. (A) Ride Report (B) Relay (C) Strava. The average number of trips was taken and the lines are color coded by the number of standard deviations from that mean to bring out the most travelled routes. GT is marked with a star.

In conjunction with the bicycle volume maps, a map of bicycle infrastructure in Atlanta was also used to develop routes. The routes were designed to have variation in facility and road type. Each route has a segment of low-stress (i.e. parks, shared use trail), medium-stress, and high stress (i.e. mixed traffic with high car volumes). The routes are located around the city, have a variety of conditions in each, and are located where people regularly ride. A map of the routes is provided in Figure 4-2.

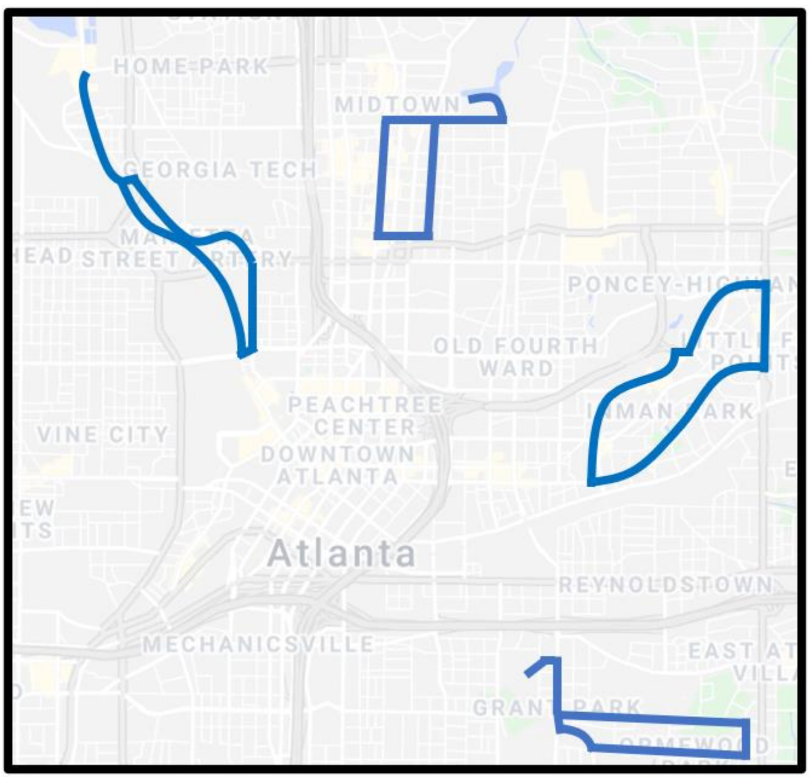

Figure 4-2 The four chosen routes in Atlanta

All Atlanta routes had more vehicular interaction than the Delft route as Dutch design standards separate cyclists and motor vehicles above 30 kph and discourage car use in the inner city (*25*). However, both locations had route segments with unprotected bicycle lanes and mixed traffic. Maps with color-coded infrastructure of the Delft route and the most frequently used Atlanta route are shown in Figure 4-3. Based on the LTS rating system, the route through Delft varied from LTS 1 to LTS 2 and the Atlanta routes LTS 1 to LTS 4. Although the routes were designed using similar principles, the availability of high stress infrastructure in Delft was very low. Therefore, it was expected for stress levels to be lower in Delft.

Familiarity was surveyed in both locations. An open-ended question was used in Atlanta but changed to a Likert-scale question in Delft. Although not perfectly comparable, most cyclists were very familiar with at least a portion of the route and familiar to very familiar with the entire route. Based on the responses, the researchers feel safe assuming that route familiarity was similar across the two samples.

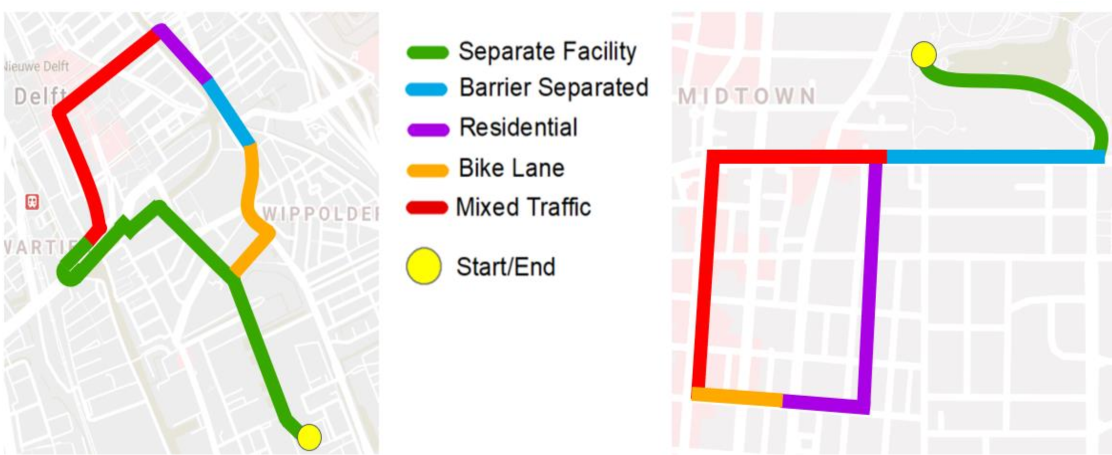

Figure 4-3 Infrastructure map of the Delft route (left) and an Atlanta route (right).

4.2.3 Recruitment/Participants

In total, there were 41 participants in Atlanta and 28 in Delft. Participants were recruited via convenience sampling through e-mails and fliers. Participants were asked to cycle one time in Atlanta, but to capture within-person differences, when possible, two times (off peak and peak hour) in Delft. In Atlanta, the participants were able to choose the time that fit their schedule best, resulting in 56% of rides done during peak hours. In Delft, 52% of rides occurred during peak hours. Ten participants in Delft were given 10-euro gift cards as compensation for participation. This was added mid-way through recruitment to encourage participation.

4.2.4 Instruments

Similar instrumentation, both in terms of surveys and sensors, were used in Atlanta and Delft. The GT instrumented bicycle components were designed to be attached to participants' bicycles, need minimal intervention from the research team once started, and have minimal impact on participants' experience biking. This resulted in the setup shown in Figure 4-4. The matrix, the green piece in the foreground, sits on the handlebars and the box is attached to a seat-mounted bicycle rack. Two cords are wound around the top tube of the bicycle to attach the two components. A bicycle equipped with the sensors is shown on the right in Figure 4-5. The matrix contains the GPS, accelerometer, gyroscope, and atmospheric sensors. The box contains the power supply, LiDAR, Sonar, and particulate matter sensors. Table 4-1 lists the sensor type, part number, and position. The primary sensors to be used in this research include the GPS and LiDAR. The instrumented bicycle in the Netherlands had a similar sensor set-up including GPS and LiDAR, but these were affixed to one bicycle that was ridden by all participants. Images of each of the instrumented bicycle setups are shown in Figure 4-5.

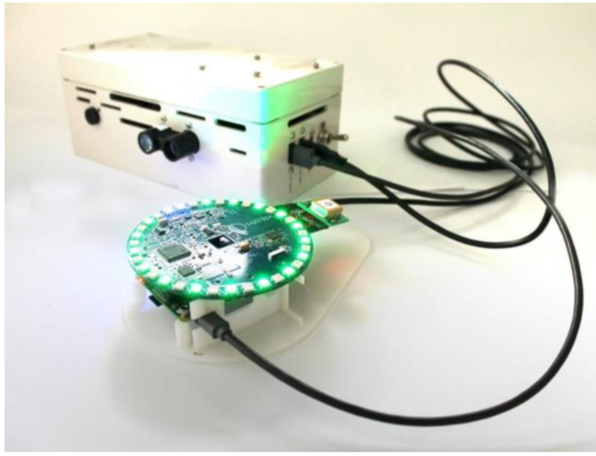

Figure 4-4 Components of the Georgia Tech instrumented bicycle

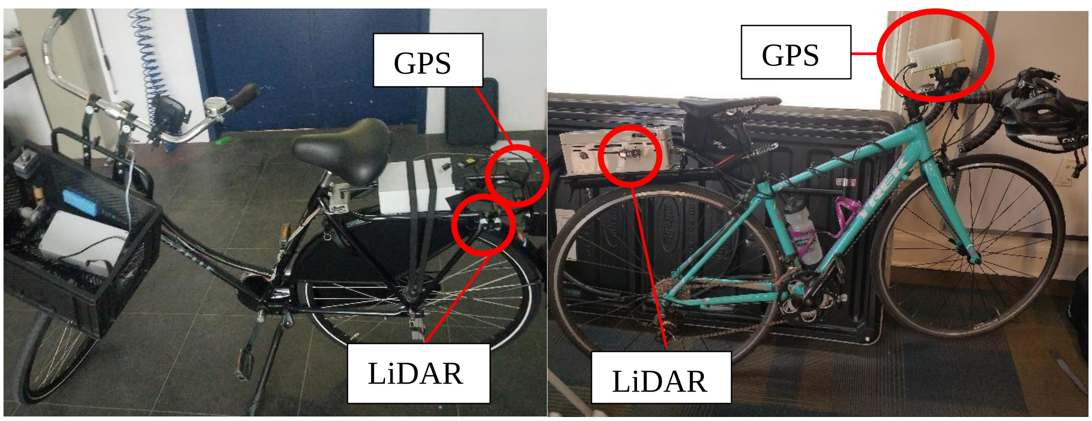

Figure 4-5 Left: Instrumented bicycle used in Delft with the sensors used in this paper identified. Right: Instrumented bicycle components used in Atlanta on the researcher's bicycle with the sensors used in this paper identified.

Table 4-1 Georgia Tech instrumented bicycle sensors

Sensor Type	Part Number	Location
Inertial Measurement Unit (IMU) (accelerometer, gyroscope, magnetometer)	ST LSM9DS1	Handlebars
Temperature/Humidity	ST HTS221	Handlebars
Particulate Matter	PMS5003	Box
Altitude	NXP MPL3115A2	Handlebars
Microphone Array	8 MEMS MP34DB02	Handlebars
LiDAR	LIDAR-Lite v3	Box
Sonar	LV-MaxSonar-EZ1	Box

The survey consisted of two parts. The first part asked questions about the cyclists' cycling habits (frequency, time cycling, etc.) and attitudes (risk taking preferences, trust of car drivers, etc.). The second part asked demographic questions such as gender identification and education level. One of the key rider characteristic questions asked cyclists to categorize themselves by a rider type defined by interest and confidence in cycling. This scale was originally defined by Geller in Portland to categorize people by what level of infrastructure was needed for them to cycle (*4*). It included 4 categories: "Strong & Fearless," "Enthused & Confident," "Interested, but Concerned," and "No Way, No How." The "Strong & Fearless" cyclists would be willing to cycle on any roadway. The required infrastructure then increases up to "Interested, but Concerned" cyclists who need full separation from motor vehicles. Misra et al. (*26*) refined the categories to include a category in the middle called "Comfortable, but Cautious." This refined scale was used for this study. The "No Way, No How" category was excluded because these people would not be willing participants in a study requiring cycling. The attitudinal questions were borrowed from a study that explored user preferences for bicycle infrastructure in emerging cycling cities and the attitudes that influence those preferences (*27*). The surveys used in the USA and the Netherlands can be found in Combined, these studies have demonstrated the value of naturalistic cycling, smooth and separated cycle tracks, and designing from a cyclists' perspective. The common thread throughout these studies was the use of naturalistic cycling in combination with sensing and surveys. These methods allowed for new insights into cyclist behavior and design.

The approach used in this dissertation combined surveys and sensing techniques in naturalistic cycling. Previous research focused on cyclists' stress focused on surveys without the naturalistic cycling component or included the naturalistic cycling without a robust survey. Using in-ride surveys allowed for cyclists to describe their stress in near real-time. Literature shows that survey responses are less negative after a cycling experience (*1*), so it stands to reason that cyclists would also respond differently to more open-ended questions in the midst of a ride.

There are two other options to collect this data that are not truly naturalistic. These would be 1) on a test track and 2) in a simulator. The three (including naturalistic cycling) have varying degrees of trade-off between closeness to reality and control over the experimental conditions. Naturalistic cycling allows for the most realistic conditions but has the least control. Although the route could be predictable for the most part, the presence and actions of surrounding road users is largely unpredictable. This unpredictability requires more trials to ensure a sufficiently large, usable dataset. A test track presents much more control than naturalistic cycling but removes much concern for safety which is an important component of cyclists' stress. Test tracks are also very costly to construct and require large amounts of space that are not typically available, especially for research on cycling. Research comparing responses in naturalistic settings and a constructed to feel realistic test track may show that a test track allows for very similar responses, but with greater control. Unfortunately, although it has the possibility of being the most effective option, the costs of constructing one are prohibitive.

The last approach would be to use a simulator. This option presents the most control, but is the least realistic. Cycling simulators suffer from missing important cues such as the feeling of the air passing the cyclist, the pressure difference of a close pass, and the feeling of turning the bicycle. A participant clearly has no concern about their safety in such an environment which may impact their stress. A benefit to cycling simulators is that a broader cross-section of the population may be willing to participate in the study. Participants who are concerned about their safety when cycling will not participate in a naturalistic study but may in a simulator study. A simulator may be the best option, if available, for studies of hazard identification or differences between "interested, but concerned" and "strong and fearless" cyclists for safety concerns and to attract participants, respectively.

The approach used in this study presents the most realistic scenarios, and thus is the best choice among these for studying cyclists' stress. The approach used here was also low-cost and allowed for use of the existing infrastructure, making it accessible to any researcher within proximity of a bike-able road. It was innovative in its combination of techniques and allowed for new insights into cyclists' stress and behavior. For some studies, a simulator may be the ideal choice, so careful consideration should be given when selecting which method to use. However, one contribution of this work was to demonstrate that in-ride surveys with naturalistic cycling and instrumented bicycles is a feasible method for studying cyclists' behavior.

Eye tracking is another research method that has infrequently been used in cycling research. The research within this dissertation demonstrated some of the benefits of the approach as well as caveats. Eye movement is influenced by many external variables such as person-to-person differences that are not immediately relevant to the study. However, it can be challenging to recruit high enough numbers of participants for a naturalistic cycling experiment to adjust for these factors. When data collection completed for the study in CHAPTER 5, it has a larger sample size than any published eye tracking in naturalistic cycling study. Because of these external sources of variability, the statistical testing resulted in few significant results when trying to describe gaze behavior in a general manner as was attempted in CHAPTER 5. Despite these challenges, some valuable insights were gleaned, particularly about the differences between cyclists' motor-tactical skills, safety motives on gaze behavior and how those differed from expectations based on literature on drivers' gaze behavior. The technique was effective as an exploratory study, but more concrete results were possible when choosing a narrower scope as was done in CHAPTER 6. The narrow, focused scope allowed for less influence from outside factors, more significant results, and more practical findings. The research demonstrated that eye tracking can be used for both exploratory studies and practical, focused studies to gather valuable findings. But, it also demonstrated that the more focused scope allows for greater control and more significant results.

In addition to findings about the methods, there were important findings about cyclists' behavior and stress. A theme that arose during the research was the value of a smooth riding surface. Although previously pavement condition had rarely been considered in studies on cyclists' stress, CHAPTER 4 demonstrated that poor pavement is one of the top three most cited stressors among cyclists. CHAPTER 5 demonstrated that poor pavement can be a safety concern as it leads to lower gaze, potentially resulting in missed safety cues that would've been seen if the cyclist had been looking further ahead. CHAPTER 6 expanded on these findings to show that the most important components of poor pavement are unevenness, potholes, debris, and wide cracking. This study also demonstrated that decreased separation between cyclists and motorists resulted in a decreased likelihood that a participant fixated on one of these pavement concerns. This emphasizes the safety concern further. This information leads to implementable maintenance strategies, such as street sweeping bike lanes and setting stricter requirements on utility maintenance patching, to improve the comfort and safety of roadway facilities for cyclists.

Furthermore, the research showed that cyclists' behavior and needs may not follow the trends expected from literature on drivers. CHAPTER 6 suggested that pavement maintenance strategies need to consider that inconveniences for a driver (i.e. a mid-sized pothole) may be a safety concern for a cyclist. CHAPTER 5 also demonstrated that the gaze behavior of cyclists did not align with expectations based on the driving literature. Again, demonstrating that when designing for cyclists, engineers and planners cannot assume that cyclists will behave a certain way based on knowledge of drivers. Cyclists need to be considered through all aspects from planning to design to maintenance, but currently they are not frequently integrated into the planning and design of projects and rarely considered in maintenance. Planning, design and maintenance for all projects where someone could conceivably cycle should endeavor to come from a cyclists' perspective, but this can be challenging for personnel who do not cycle. Agencies should endeavor to have personnel not just drive projects, but also cycle them. If possible, it would be best to have a regular cyclist contribute to projects so that the drivers' perspective is not the only contribution through planning to design. The results also showed that aspects like location, age, and rider type did not significantly impact the most important factors in cyclists' stress or their reaction to pavement features. Although a group of humans will always vary, the most important factors to cyclists' stress and comfort appear fairly consistent across cyclists making design from a cyclists' perspective more achievable.

4.3 Limitations

As with all research endeavors, this research had some limitations. Inherently, naturalistic methods are limited in the control researchers have on the setting. This allows for very realistic experiences but can lead to large amounts of noise or unexpected events to process. For example, the pothole that was supposed to be analyzed in CHAPTER 6 for the mixed traffic scenario was filled shortly after data collection began. There was another, less ideal, pothole along the segment, but similarly unwanted and unexpected situations can happen in any naturalistic study.

The research was also limited by a lack of high stress scenarios for the eye tracking data from Delft. This limited the ability to fully explore the impact of stress on cyclists' gaze behavior. Further data collection could remedy this but was not possible because of the Covid-19 pandemic restrictions. This limitation also highlights the difficulty of comparing a low-stress, established cycling environment such as Delft with a higher-stress, emerging cycling environment such as Atlanta. In some ways such a comparison provides interesting and valuable insights such as the finding in CHAPTER 4 that motor vehicles were the top stressor in both locations. However, the high-stress infrastructure was limited in Delft and the low-stress was limited in Atlanta, so equivalent routes were not possible.

Furthermore, eye tracking has been used so infrequently in studies of cyclists that a standard set of measures has not yet been agreed upon. Therefore, the eye tracker work in this dissertation tended to be exploratory in nature. The methods seem promising, but more work is needed to confirm the findings based on further usage of eye trackers in cyclist behavior studies. Both fixations and measures of gaze were used in these analyses, but due to the motion of the cyclist relative to the world, what would be a fixation in a static situation becomes a smooth pursuit. Eye tracking software is not well equipped to track smooth pursuits automatically. The largest dispersion value was used to try to accommodate this, but fixations were not as accurately measures as they would be in a static situation. Because of this limitation, the gaze measures would be more meaningful than the fixation measures and differences in measures of fixation would need to be more significant to be trusted. This limitation can be accommodated in some analyses, such as the work in CHAPTER 6 which used frame-by-frame analysis. These more micro-scale analyses can better correct for the software's limitations in detecting smooth pursuit movements.

One pervasive limitation was a lack of diversity in the study sample. Participants for all data collection efforts were predominately white and highly educated. Efforts were made to gather a more representative sample, especially for the online survey, but were ultimately unsuccessful. A lack of financial incentive for participation could partially explain these unsuccessful efforts, but predominately white and educated samples are a common limitation in studies on cyclists. Research is needed on how to obtain a more representative sample of the cycling population.

Furthermore, although the sample sizes in this research were large for a naturalistic cycling and eye tracking study, the sample sizes were still too small (< 30) for robust statistical analyses to be performed. Additionally, with such small sample sizes, it is impossible to be confident that the results are applicable to a larger population, thereby necessitating repeat studies to confirm the results.

4.4 Future Work

This dissertation has pointed to a few areas for future research. The results overall demonstrated the value of eye tracking, instrumented bicycles, and in-ride surveys for better understanding of cyclists and possibly other road users' stress and behavior. Future research can continue to use these methods to study road users' feelings of stress, safety, and comfort and how they behave in and interact with their environment.

The methods and data from CHAPTER 4 could be used to go a step further by incorporating the maps to better understand exactly what infrastructure existed where the cyclists commented on stressors. Additionally, these maps could be aggregated to identify stress hotspots. Furthermore, this study could be repeated in better matched cities in terms of size. Atlanta is a large city and Delft a small city, so comparison to larger Dutch cities such as Amsterdam or Rotterdam could be beneficial. Further, finding more comparable routes, if possible, could further address the limitations of this study.

The instrumented bicycle as a tool for understanding cyclist behaviors also has more potential. For example, the sonar could be used to better understand how fast vehicles are going during close-pass events and further illuminate why some close-pass events are not considered stressful. The question of cyclists' speed could also be further studied by having the same cyclist ride in separated and mixed settings. Another potential study would be to study off-peak and peak hours using these methods. Data were collected to conduct such analysis in Delft, but as a small college town, peak hour traffic and stress levels did not vary enough from off-peak hours to finish the study.

CHAPTER 5 was exploratory and opened the door to many future avenues for research. The results suggested that stress may influence gaze, but a future study with a more even distribution of stress levels on the route is needed to build more confidence in the findings. Complexity could be studied in a more controlled environment with non-visual tasks increasing the complexity. Overall, the strongest influence on gaze behavior in CHAPTER 5 was skill. Confidence in the results could be increased through further exploration with a larger sample in each skill group. Furthermore, the results suggested we cannot assume that what is known about drivers' gaze will be the same for cyclists. Little research to date has focused on cyclists' gaze behavior, but many of the studies of drivers' gaze behavior could be repeated for cyclists. In addition, a study of cyclists' gaze behavior in simulators compared to in-field could inform whether these future gaze behavior studies could be performed in the highly controlled environment of a simulator instead of in-field.

The analysis in CHAPTER 5 did not take into consideration the cyclists' speed or time series analysis, but both warrant future study. A recent paper using eye tracking data collected after that in this dissertation found that risk perception had an influence on speed and combined these had an influence on cyclists' gaze patterns (*2*). The cyclists' gaze tended to be higher and more on the travel path when cycling fast and they went slower when their risk perception was higher. Risk perception is a component of cyclists' stress, so it may also be worth looking at stress, cyclists' speed, and if they have the same relationship to gaze patterns. A validation-type study that determines the validity of fixation measurements at varying cycling speeds would also be very valuable. To the algorithm, fixations would look like smooth pursuits. The algorithm assumes the eye trackers are stationary, so the world is moving relative to the eye trackers, which can result in errors identifying fixations. Speed may impact the error resulting from this.

Another analysis method that could be used to build on this dissertation is time-series analysis. Time-series analysis in combination with areas of interest analysis has been used in a previous study of cyclists' gaze behavior to identify common gaze patterns (*3*). The paper was brief conference paper and had a narrow scope analyzing just 1 intersection. However, it demonstrated the value of time-series analysis for identifying repetitive gaze patterns. It is possible that more stressed cyclists tend to shoulder check more frequently or very rapidly and briefly look away from the travel direction when scanning. Although the gaze area was explored in this dissertation, the use of time-series analysis could better illuminate the gaze patterns that resulted in those gaze areas.

CHAPTER 6 also suggested a couple directions for future work. This dissertation laid out the most important pavement distresses and gave ideas for incorporating the information into asset management plans. However, the next step would be to develop a model of pavement deterioration on cycle facilities. Pavement deterioration on major auto-focused assets has been extensively researched, but less is known about lower volume roads and bicycle facilities. This information is critical to asset management plans. Additionally, eye tracking can demonstrate that a cyclist has or has not fixated on an object, but it cannot definitively inform whether the cyclist has processed that information. A simulator-based study could take the research a step further to determine if the reduced fixations in mixed traffic settings are indicative that the cyclist is missing these safety-critical cues.

4.4.1 Considerations/Adjustments to the Instrumented Bicycle

In the process of this research, I identified ways in which the instrumented bicycle could be improved. The first involves redundancy. For any future data collection with the instrumented bicycle, I would recommend building in redundant components for any of the most critical sources of data. For example, I needed a redundant camera that could serve to both help identify where the cyclist was in the case of lost GPS data and provide footage if the eye tracking data were corrupted. Having redundant data allows us to make meaning out of the data even if one system has failed.

One component related to redundancy that could be valuable in future studies would be a speedometer. Speed can be derived from the GPS data, but the GPS frequently produced invalid data, likely attributable to the tall buildings in Atlanta. Building in a speedometer would allow for gathering speed data without concern around accurate/usable GPS data.

If a future study wanted to use the instrumented bicycle to look at close-pass events, it would be very valuable to have camera data that is linked to the LiDAR and Sonar data. For the inspection of close-pass events in this dissertation, I identified all close-passes, then used the timestamp to link to the GPS data, then watched the video around that location based on my knowledge of the route. Watching the video was necessary to confirm the object close to the rider was a car and not me or some other irrelevant feature. This process would be much quicker and more accurate if there were, for example, a timestamp linking the video to the LiDAR. In addition to being faster and more accurate, this method would also eliminate the risk of invalid GPS data breaking the chain.

The eye trackers were not a practical measure of stress. Extracting stress among all the other influencers of gaze was time consuming and did not come out as significant. In my opinion, the effort would not be worth the improvement over measures of stated stress. I suspect based on my experience of working with human subjects, that a button system for identifying their stress levels may be too complicated to get participants to use. I think the best option would be a microphone setup that either cues the cyclist to give a stress rating or allows them to narrate their ride. Another idea would be to use a peripheral detection task to study their mental workload. A peripheral detection task does not work with wearable eye trackers as they stand, so that would need a separate study. If eye trackers are used, it should be for a specific purpose, directly related to the research questions, and the analysis should be tested and defined prior to beginning data collection. This is heavily dependant on the intended research questions.

Other sensors that could produce value include light (lux), cadence, and brake sensors. The light sensor would add value for an eye tracking project to remove the influence of adjusting light levels on the pupillometry data. Cadence and brake sensors are frequently used in instrumented bicycle studies (*4*) and could add valuable information about the cyclists' behavior. However, I do not think these add sufficient value to change the setup to not be attachable to anyone's bike.

The choice of sensors is heavily dependent on the study being performed, so the value of each sensor and any associated trade-offs from adding it are really determined by the study itself. I strongly recommend anyone using an instrumented bicycle for research to thoroughly test every step of the research design. It is not sufficient to just test that the sensors work, but it is critical to also check the data is coming out in a usable format for your future data analyses. Thus, the way the data will be analyzed needs to be known (and tested) before the data collection protocol and sensor selection is finalized.

Finally, I have some recommendations on build and output. It is critical that the attachment mechanism to participants' bicycles is firmly holding the box in place. In this study, the box would sometimes shift sideways when a cyclist mounted/dismounted. I tried to correct this as much as possible, but the LiDAR data would be substantially more trustworthy if the box did not change position on the cyclists' bike. Additionally, because the GPS data failed sometimes, it was extremely challenging to separate files from days where multiple rides occurred. It would be much easier to manage the data if a new file were created every time the system is started.

In summary, my key lessons from using the instrumented bicycle are 1) test everything, 2) include redundancy whenever possible, and 3) the design depends on the study. A study design that has targeted research questions, has been tested through the analysis portion, and has redundancy built in for key sensors will reduce data loss and allow for smoother, more useful data analysis.

4.5 References

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APPENDIX A. US Survey and Appendix B. NL Survey, respectively.

All survey questions used in Atlanta were also used in Delft with small adjustments to address changes in location (“Atlanta” changed to “Delft”) and structures (i.e. level of education). The familiarity question was adjusted after data collection in Atlanta from an open-ended question to a Likert-scale to be more consistent and comparable for future data collection.

During the ride, the cyclist was asked to color-code by stress level (low, moderately-low, moderately-high, and high) a map of the recently ridden segment of the route. To reduce recall error, the map was color-coded at two points during the ride and at the end. The post-ride interview inquired about the map to understand why the cyclist gave the stress ratings they gave. The data gathered in this format was the basis for the thematic analysis. An example of a digitized stress map is provided in Figure 4-6.

Figure 4-6 Example of a completed and digitized stress map

4.5.1 Protocol

The protocol of a data collection appointment started with consent forms, as approved by the human research ethics boards for both universities. Following consent, the written survey was filled out by each participant. Prior to the appointment, the participant was provided a map of the route, and the route was reviewed before the sensors were set up. Once the sensors were prepared and the participant was comfortable, the ride began. The participant cycled in front with the researcher behind in case of emergencies, sensor failure, and to give directions as needed. The participant was encouraged to not interact with the researcher and cycle as they normally would cycle. The participant and researcher stopped at two pre-designated locations along the route to colour-code the map based on their stress levels and review the directions for the next segment of the route. Once the whole ride was complete, the researcher removed the sensors and conducted the post-ride interview.

4.5.2 Analysis Method

The analysis was conducted using mixed methods. Quantitative statistical analysis primarily consisted of Mann Whitney testing of the demographic and attitudinal differences in the samples. Such quantitative analysis was limited due to the small sample size in each location. To supplement the quantitative analysis, thematic analysis was used to identify and describe attitudes and ideas in interview responses. Thematic analysis is used in the field of transportation engineering to analyse open-ended survey questions (*28*), interviews (*29*, *30*), and focus groups (*31*). Braun and Clarke's article on thematic analysis was used as a guide for this analysis (*32*).

Braun and Clarke suggest four phases of thematic analysis: data familiarization, generating initial codes, finding themes, and reassessing themes (*32*). To familiarize themselves with the data, the researchers repeatedly read the data. After familiarizing, initial codes were generated to describe interesting topics in the data. The participants' responses were coded as short phrases (i.e. low traffic, smooth road surface, negative response to motor vehicles, etc.). More than one code was possible per response as participants may list more than one reason for their stress rating. The codified responses were compiled by participant. In total, 43 codes were generated. Then, themes were generated from the codes by grouping and consolidating them to a list of themes. After finding the themes, they were reassessed for coherence. To ensure the analysis was performed in a systematic manner, it was checked by two other researchers and adjusted accordingly.

An inductive (bottom-up) and semantic approach was taken to identifying themes. This means the themes were identified through exploring the responses, not from theoretical, existing knowledge found in the literature. Once the thematic analysis was complete, quantitative results from the written surveys were paired with the themed interview responses to explore the relationships of cyclist characteristics and attitudes with stated causes of stress. In addition, the instrumented bicycle data (GPS and LiDAR) were used to support the findings in the quantitative and thematic analyses.

4.5.3 GPS and LiDAR

GPS and LiDAR were equipped to both instrumented bicycles. The GPS provided location and speed data and LiDAR provided the distance to the nearest object to the left. The LiDAR were in approximately the same position on both bicycles, as shown in Figure 4-5. The GPS data were used to find cyclists' point speed to better understand riding speed in relation to stress. The LiDAR data was used to identify close-passes (a reading of under 1000 mm). Video data corresponding to these potential close-pass events were reviewed to confirm the close-pass events. Then the close-pass locations were compared with the stress maps and survey responses to explore any potential relationship between attitudes, characteristics, and stress ratings to a close-pass event.

4.6 **Results**

This section covers the results from the various analyses. First, the multiple-choice responses and reported stress levels are presented. Second, the interview responses analyzed through thematic analysis are discussed. Then both analyses are combined to explore relationships between participants' multiple-choice responses and stated causes of stress. Finally, the sensor data from the instrumented bicycle are used to tie findings in the previous results subsections to objective data.

4.6.1 Multiple-Choice Responses

Although the sample in Delft primarily consisted of graduate students from TU Delft, the two samples had similar demographic breakdowns. Mann-Whitney tests were used to find which demographic and attitudinal questions revealed a difference in the sample. Due to the small sample sizes, some true differences may not reach statistical significance. The comparisons here are meant to improve understanding of the samples, but the differences in samples and the differences in location suggest that the responses from the two samples cannot be strictly compared.

The sample was about 2/3 male and nearly all possessed the equivalent of a bachelors (25%) or graduate degree (71%). In terms of demographics, the only statistically significant difference between Atlanta and Delft was in age ($U = 21$, $p = .04$). The genders, tested with a Fisher's Exact test ($p=0.57$) were not significantly different.

The Atlanta sample had a more even spread of ages with more people above 34 years old, although both samples had the largest group in the 25-34 age range (82% in Delft and 31% in Atlanta). In the Netherlands, people were asked to ride during peak and off-peak hours, making it challenging for people with day jobs and thus, attracting more student-aged participants. To ensure this age difference did not influence the results, the results in the thematic analysis were compared by age within the Atlanta sample, showing no systematic difference in themes. Based on this finding, the authors chose not to explore age further.

When questioned about rider type, the Atlanta sample had more cyclists rating themselves as "Strong & Fearless" (39%) than the Delft sample (15%) with more people selecting "Enthused & Confident" in Delft (68%). Just under 20% in both locations chose "Comfortable, but Cautious," and none chose the "Interested, but Concerned" category. The differences did reach statistical significance ($U=21$, $p=.04$). Figure 4-7 displays the distribution of the responses.

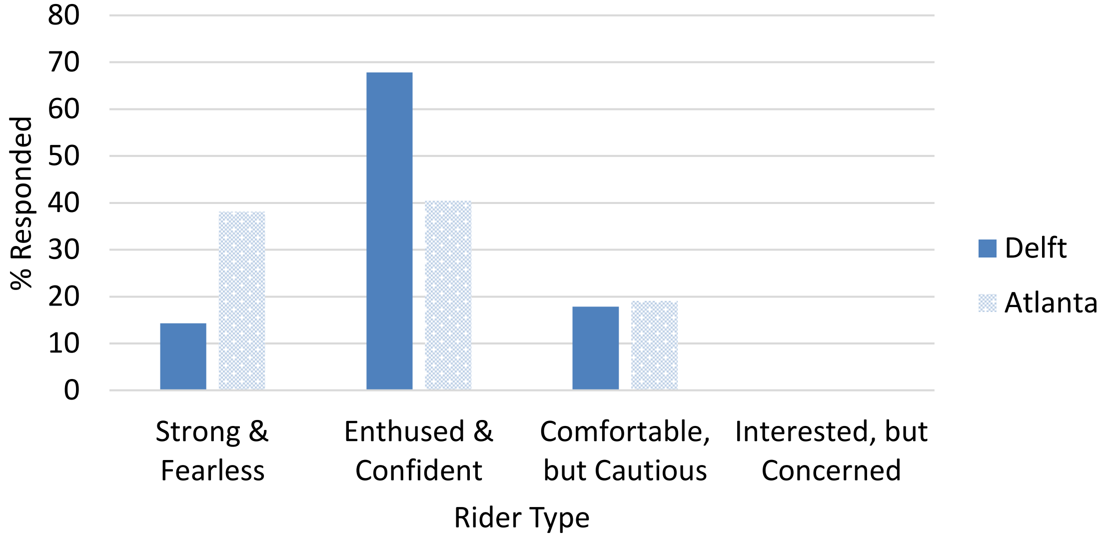
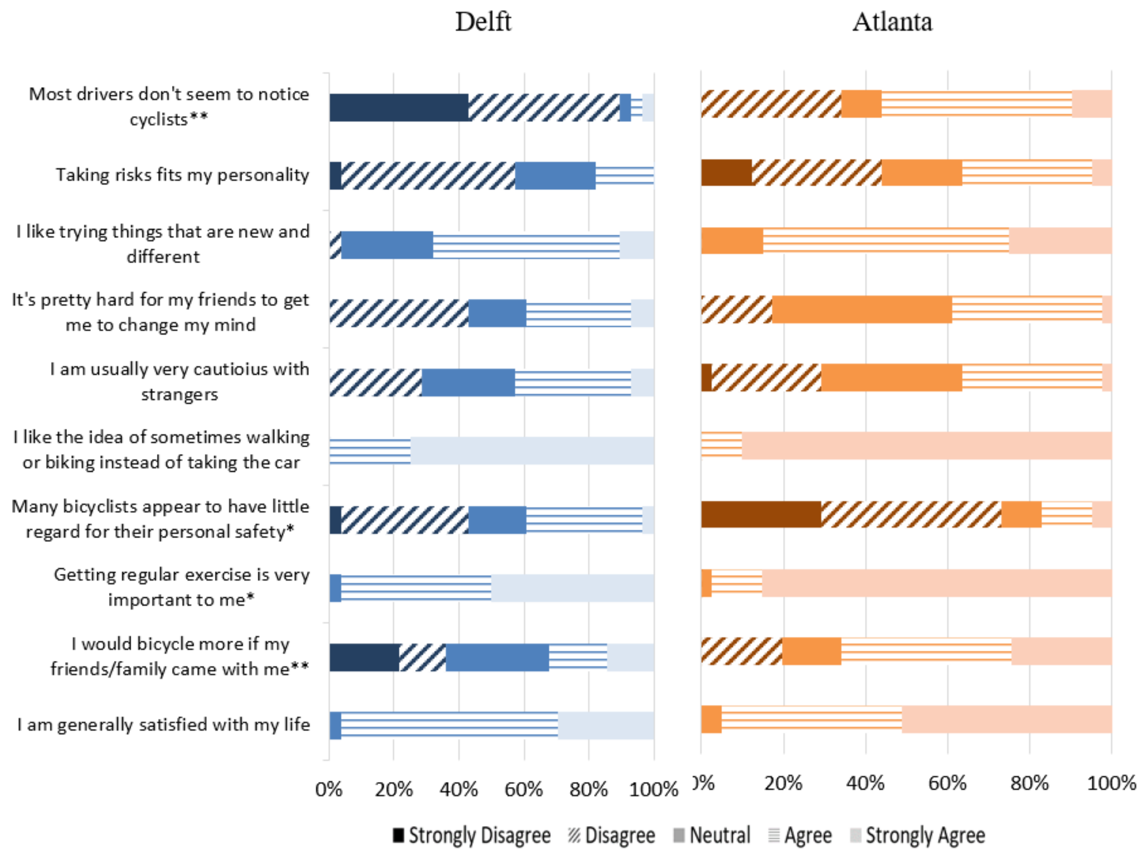


Figure 4-7 Distribution of rider type self-classification

The two samples had similar cycling experience (U=10, p=.12) with almost all participants learning to cycle as children. The Delft sample cycled for commute purposes more frequently (U=21, p=.03), but both samples primarily consisted of regular bicycle-commuters. This is an expected bias through self-selection into the experiment. The "Less than Once per Month" participants, all in Atlanta, were checked for differences in their identified themes, but no systematic difference was found. Of the ten attitudinal questions in the survey, four showed statistically significant differences. The results for the attitudinal questions are shown in Figue 4-8 with Delft on the left and Atlanta the right. The samples did not differ in their tendency towards risk-taking and their preference for alternative modes.



Figue 4-8 Results of attitudinal questions for Delft and Atlanta. Asterisks indicate statistical significance level when comparing Delft and Atlanta data (* p<0.05; ** p< 0.01 ; *** p < 0.001)

The questions on which they did differ were related to their motivations for cycling and their opinion of other road users. The most statistically significant difference (U=49, p = .008) was that cyclists in Delft tended to disagree more with the statement “Most Drivers Don’t Seem to Notice Cyclists.” The importance of this difference will be explored in the next sections (3.3, 3.4). The samples also differed statistically on the importance of exercise (U =21, p=0.03), estimation of cyclists’ regard for their own safety (U=21, p=0.03), and whether their friends or family cycling with them would make them more likely to cycle (U=45, p=.009). These latter three could be associated with the higher cycling modal share in the Netherlands.

Overall, the samples do differ, but these demographic differences do not seem to be the primary influence on the themes stated in their interviews. Age and commute frequency were checked, and no clear systematic difference was found in their thematic analyses. The highly statistically significant difference in response to “Most Drivers Don’t Seem to Notice Cyclists” will continue to be explored throughout the analysis.

4.6.2 Comparison of Stress Levels

As expected, the percentage of segments considered by cyclists as ‘low stress’ was higher in Delft than Atlanta. The stress ratings by percentage of segments are shown in Figure 4-9.

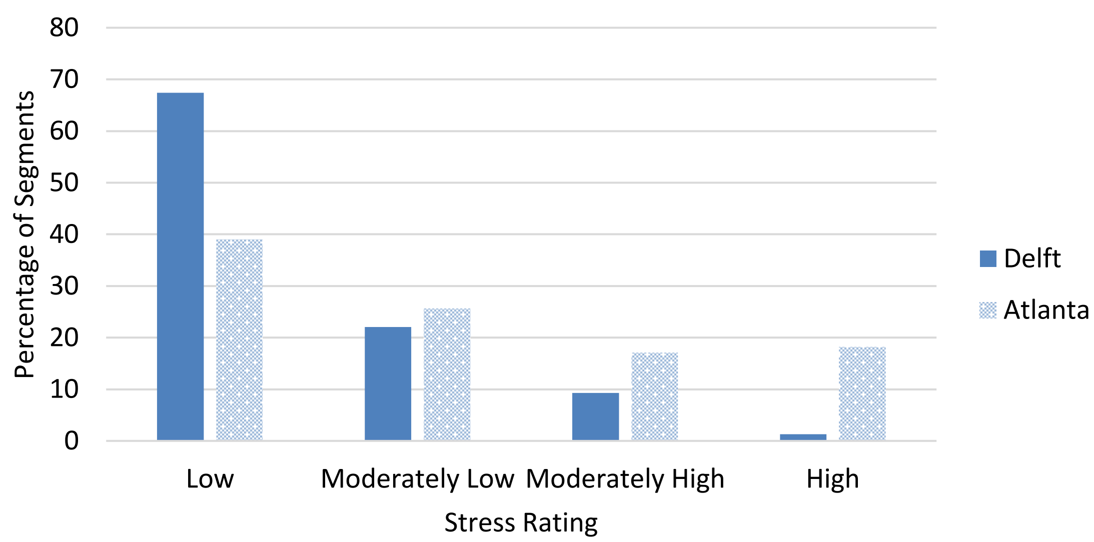


Figure 4-9 Distribution of stress ratings by segment for Delft and Atlanta

4.6.3 *Thematic Analysis*

This section covers the results from the thematic analysis and the combination of the thematic analysis results and cyclists' characteristics.

4.6.3.1 Interview Thematic Analysis

Twelve themes were identified for causes of stress; the most frequently mentioned were motor vehicles, pavement (road surface), and infrastructure. Nine themes were identified for stress reducers; the most frequently mentioned were high quality road infrastructure, low traffic volumes (both motorists and cyclists), and familiarity of the route/environment. Due to the low sample size and sample differences, Atlanta and Delft were not quantitatively compared, but compared qualitatively to highlight interesting results. Table 4-2 shows the percentage of participants who mentioned each theme in their interviews.

Table 4-2 Summary of the thematic analysis showing percentage of respondents mentioning each theme

Theme	**Delft**	**Atlanta**	**Total**
Causes of Stress			
Motor Vehicles	68%	93%	83%
Poor Pavement	54%	71%	64%
Poor Infrastructure	32%	78%	58%
High Volume	29%	54%	43%
Anticipation	4%	46%	29%
Speed Differential	18%	34%	28%
Lane Restriction	32%	22%	26%
Surprises	32%	17%	23%
Bus/Truck	21%	22%	22%
Pedestrians	32%	15%	22%
Cyclists	36%	0%	17%
Intersections	14%	10%	12%

Table 4-3 Approved

Reducers of Stress			
Quality Infrastructure	93%	80%	86%
Low Volume	89%	71%	78%
Familiarity	75%	29%	48%
Speed Differential	29%	41%	36%
Lack of Motor Vehicles	29%	37%	33%
Good Pavement	32%	17%	23%
Ambiance	11%	17%	14%
Lack of Pedestrians	4%	5%	4%
Lack of Intersections	7%	0%	3%

The top three stressors in each location were not the same. Motor vehicles were the top stressor in both locations. In Atlanta poor road infrastructure (78%) slightly outdid poor road surface (71%). It is notable that poor road infrastructure was mentioned over twice as often in Atlanta (78%) as in Delft (32%). In Delft, poor road surface (54%) was the second most common stressor. However, other cyclists were the third highest stressor (36%) in Delft with pedestrians, lane restriction, and surprises tied with poor infrastructure (32%) for fourth most common. The differences in percent identifying other cyclists and pedestrians as stressors likely have to do with the relatively higher modal share of cycling and walking in Delft than in Atlanta. Another notable difference was the mention of anticipation, the fifth most common in Atlanta (46%) and least common in Delft (4%). These comments were mostly about the movements of other road users, especially motor vehicles in Atlanta. It is notable that anticipating driver movements was so different given that motor vehicles were the most mentioned stressor in both locations.

The top two stress reducers, high quality infrastructure and low volumes, were the same in both locations. The third highest in Atlanta (41%) was speed differential with familiarity (29%) as the fifth most common. However, familiarity was the third most common in Delft (75%). As mentioned, familiarity with the route was similar between both samples. Nonetheless, to check for the effect of familiarity, all participants who did not rate any segment as very familiar were temporarily removed from the dataset, leaving 30 participants in Atlanta and 27 in Delft. In this reduced dataset, cyclists in the Netherlands still mentioned familiarity almost twice as frequently (78% in Delft and 40% in Atlanta)

Although the Atlanta participants would have encountered a far larger number of vehicles due to modal share and infrastructure differences, motor vehicles were the most mentioned stressor in both locations. 93% of participants in Atlanta mentioned motor vehicles, and fewer participants, 68%, mentioned them in Delft, which is expected due to higher stress levels and vehicle volumes in Atlanta. Overall, 83% of participants mentioned vehicles as being a cause of stress and 33% specifically mentioned the lack of motor vehicles as being a reducer of stress.

Quality infrastructure was the top stress reducer. 86% of participants mentioned something about the infrastructure as being a stress reducer, many of these mentioning "separation from motor vehicles," the width of the road, and, in Atlanta, multi-lane roads that allowed vehicles to pass. About ¼ of the participants mentioned restriction of their lane by other road users, labelled lane restriction, such as a close-pass or wrong-way cycling, as a stressor. These results suggest that cyclists appreciate infrastructure that limits their interaction with other road users, especially motor vehicles, and when not possible, provides space to allow for comfortable passing distances.

Infrastructure was both a high-ranking stressor and stress reducer. Infrastructure consists of many components. Therefore, multiple aspects of infrastructure have been broken out in Table 4-4. Aspects of infrastructure chosen for detailed analysis included: width, number of travel lanes (only relevant in Atlanta), presence of bicycle facilities, and sight distance. In addition, the impact of parked vehicles, one aspect of the motor vehicles theme, is also included in the detailed analysis.

As shown in Table 4-4, the lack of a bicycle facility was never a complaint in Delft but was frequently mentioned in Atlanta (34%). The high mention of narrowness in Delft (29%) was related to a narrowed section from construction along the Delft route. Width overall of the available travel space for cyclists likely varied between the two locations but was mentioned about equally as a stress reducer (~12%). The presence of a bicycle facility was appreciated by both samples and served to reduce stress. Good visibility was mentioned about 14% of the time in Delft, but never in Atlanta. In Delft, sight distance was more important than width to reducing cyclist stress. The number of travel lanes was only slightly more frequently mentioned as a stressor (10%) than as a stress reducer (7%). Common understanding is that number of lanes contributes significantly to stress, but when cycling in mixed traffic, cyclists in Atlanta appreciated that motorists were able to move to another lane to pass them. Both groups mentioned parked vehicles at about the same rates (~17%) and both routes had similar roadside parking availability. Although cyclists in Delft believe drivers notice them more frequently, they seem to have similar wariness around parked vehicles as Atlanta cyclists.

Table 4-4 More detailed themes showing percentage of respondents mentioning sub-themes within the infrastructure and motor vehicles themes

Theme	Delft	Atlanta	Total
Causes			
Sub-theme of Motor Vehicles			
Parked vehicles	18%	17%	17%
Sub-theme of Infrastructure			
Narrow	29%	17%	22%
Number of Travel Lanes	0%	10%	6%
No Bicycle Facility	0%	34%	20%
Sight Distance Issue	4%	7%	6%
Reducers			
Sub-theme of Infrastructure			
Wide	11%	12%	12%
Number of Travel Lanes	0%	7%	4%
Bicycle Facility	29%	39%	35%
Good Sight Distance	14%	0%	6%

For this analysis, the speed differential theme was defined as a mention of either their own speed or the speed of other travelers. Just over ¼ of participants mentioned speed differentials as a stressor and even more (36%) mentioned it as a stress reducer. Higher speed differences were associated with higher stress. Although both sets of participants mentioned speed, Atlanta cyclists mentioned it about twice as frequently and the focus of the comments differed between the two samples. In Delft, the comments were about the cyclists being able to keep (or not keep) their preferred speed. For example, one cyclist in Delft said the reason for their low stress rating on all segments was the “chill speed so [they] had more time to analyze and anticipate.” In contrast, in Atlanta the responses were about the speed of the vehicles. For example, stress was reduced by “lots of stop signs to slow cars,” “stop and go traffic,” and “traffic flow going [participant’s] speed.” Stress was increased by “fast cars”. Both perspectives ultimately reveal that cyclists are less stressed by low speed differentials and not be pressured by speed differentials to deviate from their ideal speed.

It is also worth noting that ambiance was mentioned by 11% of cyclists in Delft and, even more, 17% in Atlanta. Ambiance included comments about their surroundings unrelated to the immediate transportation needs such as having trees along the path or a nice view. Although not a main stress reducer, it was mentioned without prompting suggesting it is a factor in cyclist stress and could warrant future study.

4.6.3.2 Combining Interviews with Attitudes

By combining interview responses with the attitudinal questions in both locations, we examined relationships between cyclists’ attitudes or rider type to their stated stressors. The low cell frequencies do not allow for statistical testing but suggest some interesting associations that could be further investigated with larger samples.

The first relationship explored was between how people responded to “Most Drivers Don’t Seem to Notice Cyclists” and mention of motor vehicles as stressors. Figure 4-10 breaks down the results by location with the bars displaying the number of people who mentioned motor vehicles as stressor in each location grouped by their response to the attitudinal question. Of those agreeing or neutral to this statement, 97% mentioned a motor vehicle. However, of those disagreeing with this statement only 64% mentioned a motor vehicle. This suggests that cyclists who disagree with “Most Drivers Don’t Seem to Notice Cyclists” may be slightly less likely to mention a motor vehicle as a stressor. However, with more cyclists in Atlanta agreeing and in Delft disagreeing, this could also be related to regional differences.

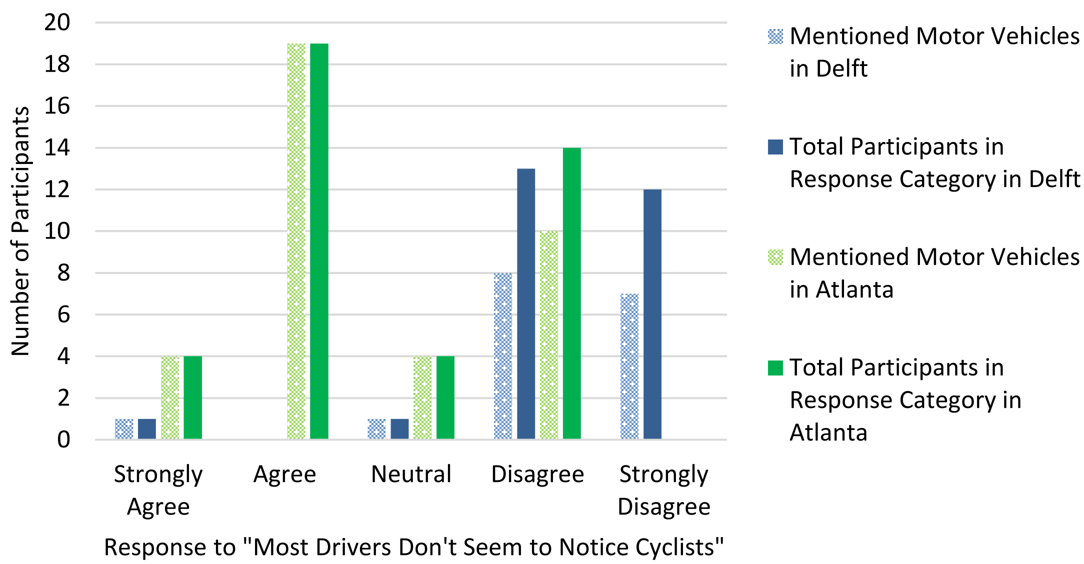


Figure 4-10 Number of people responding to each category of “Most Drivers Don’t Seem to Notice Cyclists” who mentioned a motor vehicle as a stressor in the interview

The second relationship explored was between rider type and mention of motor vehicles, including buses and trucks, as a stressor. No obvious relationship existed with about even percentages (~70-80%) in each category in both places. Ultimately, motor vehicles appear to be a stressor for most people.

The third relationship was between rider type and mention of the infrastructure as either a stressor or stress reducer. There did not seem to be any obvious trend suggesting that

"Strong & Fearless" cyclists mentioned infrastructure more or less than the "Comfortable, but Cautious" riders.

Three more relationships were explored to understand why almost exclusively, cyclists in Atlanta anticipated other road users' movements. Although in Delft cyclists were surrounded by other cyclists, they did not report anticipating cyclist movements at the rate Atlanta cyclists anticipated driver movements. This suggests Delft cyclists were confident in predicting the movements of other cyclists, but Atlanta cyclists were not confident in predicting motorists' actions. We decided to explore what characteristics of Atlanta cyclists correlated with commenting about anticipating a driver movement. Rider type, responses to "Most drivers don't seem to notice cyclists," and commute frequency were compared. Rider type and the attitudinal response did not show a relationship with anticipating driver actions, but the daily commuters mentioned this theme substantially more (14 of the 21 daily commuters) than the less frequent commuters (5 of the 30 others).

4.6.4 Comparison of the Sensor Data

LiDAR and GPS are useful sensors for measuring key components of the cycling experience including speed and proximity to motor vehicles. These data are used in this section to further explore the stress responses regarding motor vehicles and speed differentials. LiDAR data was used to measure close-pass events in which a motor vehicle passes a cyclist with less than 1 meter of space. Three assumptions were checked with regard to close-passes: (1) cyclists in Delft are less likely to rate a close-pass event as high stress, (2) cyclists with a higher comfort rating (i.e. strong and fearless) are less likely to rate a close-pass event as high stress, and (3) cyclists who disagreed with the statement that “Most drivers don’t seem to notice cyclists” are less likely rate a close-pass event as high stress.

In addition, GPS sensor data were used to understand cyclist speed by taking the instantaneous speed from GPS reading to GPS reading. This speed data can be used to check the assumption that cyclists in Delft cycle slower than the cyclists in Atlanta. This hypothesis is suggested by the comments about cyclists being able to keep their own speed in Delft.

4.6.4.1 LiDAR

The LiDAR data were used to identify locations with close-passes, with results shown in Table 4-5. Only four close-pass events were found in the Atlanta data and seven in the Delft data, two during the same ride (labelled 3 and 4). 4 of the 7 close-pass events in Delft were rated low stress, two of which were within a closer distance than any of the close-pass events in Atlanta. 4 of the 7 close-pass events in Delft were with a bus, 2 of which were rated low stress. The segments where these close-pass events occurred were along one-way streets with an exception for cyclists. The cyclists were going against the flow of traffic when passed by the buses. During the other close-pass events the cyclist and motor vehicle were travelling in the same direction. The narrow one-way street, low speed limit (30 kph), and nearby pedestrian areas likely resulted in low speeds (lower than the speed limit) of the motor vehicles in this area. In this unique situation, it seemed that cyclists were more tolerant of a close-pass event, likely at least partially due to low speeds.

In Atlanta, the close-pass events were all rated above low stress. Most happened at a distance greater than those in Delft. The conditions of the close-pass events were such that they were always on mixed traffic segments with the motorist and cyclist moving in the same direction. The speed limit on the roads with close-pass events was 25 mph (40 kph).

The relationship between rider type and the responses to “Most drivers don’t seem to notice cyclists” to their stress rating during a close-pass event was explored and is presented in Table 4-5. However, there does not seem to be any link with rider type. The strong polarization of answers to “Most drivers don’t seem to notice cyclists” resulted in all cyclists experiencing a close-pass event in Delft on the disagree side and all in Atlanta on the agree side. A larger sample of close-pass events with a more diverse sample regarding this question may be necessary to determine if it is related to their belief that drivers notice them. However, it should be noted that in addition to the low speeds, the difference in stress rating of close-pass events, could be related to these different views of whether drivers notice cyclists.

Table 4-5 Close-pass events and characteristics of the pass and rider

Delft Close-Pass	Bus	Distance	Rider Type	"Most drivers don't seem to notice cyclists"	Stress Rating
1	No	850 mm	Strong & Fearless	Disagree	Low
2	No	720 mm	Enthused & Confident	Disagree	Low
3	Yes	580 mm	Comfortable, but Cautious	Strongly Disagree	Moderately Low
4	No	670 mm	Comfortable, but Cautious	Strongly Disagree	Moderately Low
5	Yes	620 mm	Enthused & Confident	Disagree	Low
6	Yes	610 mm	Comfortable, but Cautious	Strongly Disagree	Low
7	Yes	600 mm	Enthused & Confident	Strongly Disagree	Moderately high
Atlanta Close-Pass					
1	No	710 mm	Comfortable, but Cautious	Strongly agree	Moderately high
2	No	900 mm	Enthused & Confident	Agree	High
3	No	710 mm	Strong & Fearless	Agree	Moderately low
4	No	700 mm	Enthused & Confident	Strongly agree	Moderately low

4.6.4.2 *GPS*

Based on the findings that cyclists appreciated getting to travel at their ideal speed, and that the Atlanta cyclists were more frequently stressed by high speed differentials, it was assumed that cyclists in Delft would cycle slower than cyclists in Atlanta. The point speed data were plotted as boxplots in Figure 4-11. The data suggest this assumption is correct. The mean speeds are substantially different with Atlanta's mean speed (24 kph) being about twice as high as Delft's (12 kph). When looking at the median speeds this becomes even more extreme with Delft's at 7 kph and Atlanta at 27 kph. The differences could be exaggerated by plotting the point speed data (a slow-moving cyclist will generate more data points in the same distance). However, the data suggest that cyclists in the Netherlands without the pressure to move more quickly, are choosing to use a lower speed than in the United States where cyclists must ride mixed with vehicles. Although these differences are striking, the cyclists' speeds were within the range of expected values for each country (*33*). There may also be other factors influencing these speed differences. These differences may be more pronounced due to the differences in bicycle used, as cyclists in America will often use a faster bicycle than the typical Dutch city bicycle used for the experiment in Delft. Similar to the bicycle styles, American cyclists are also often more sporty than in the Netherlands where cycling is a casual, every day experience (*34*).

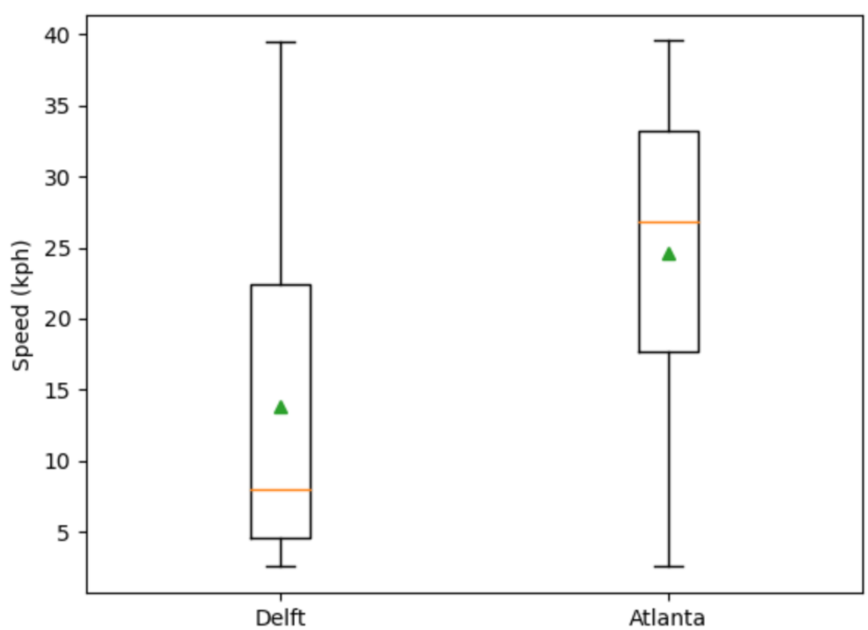


Figure 4-11 Boxplots of the speed data in kilometres per hour, triangles represent the means

4.7 Discussion

Overall, the main components of cyclist stress can be attributed to the presence of motor vehicles, poor pavement, and poor infrastructure. This section goes into further discussion about the individual results of the study and how, ultimately, they relate to the influence of the built environment on feelings of stress.

The two samples differed significantly in their responses to “Most drivers don’t seem to notice cyclists” with more agreeing in Atlanta and disagreeing in Delft. This is similar to previous findings that Dutch cyclists rated their tolerance and consideration for other road users higher than cyclists in the USA (*35*). Strictly looking at the Dutch, Dutch cyclists also reported to be very often confident that drivers notice them (*36*) and both cyclists and motorists expected motorists to yield more than cyclists (*37*). In Delft, people disagreed more with “Most drivers don’t seem to notice cyclists” and experienced lower LTS infrastructure and vehicular volumes; however, motor vehicles were still the top stressor in both Delft and Atlanta. This highlights the importance of motor vehicles to cyclists’ stress. It is well established in the literature that cyclists’ perceived safety and stress levels are negatively influenced by interaction with motor vehicles (e.g. (*31*, *38*, *39*)).

However, the Delft data suggests that it is not just motor vehicles, but all other road users that are causes of stress for cyclists. In Delft, other cyclists were the third most common stressor and pedestrians were tied with three others for the fourth most common stressor. This supports building separated infrastructure to minimize interaction with other road users, although interaction with other cyclists is likely inevitable. Additionally, it is worth noting that despite pedestrians and cyclists being frequent stressors in Delft, about twice as many participants mentioned motor vehicles than either other mode.

Another difference highlighted in the thematic analysis was how cyclists mentioned speed differentials. Delft cyclists mentioned their own speed and Atlanta cyclists mentioned vehicle speeds. Both suggested that cyclists prefer to go at their ideal speed. Based on the interview responses, the Atlanta cyclists experienced higher, more stressful speed differentials which may have pressured them to go faster than their ideal speed. This was explored in the results section (3.4.2), and it was found that the Atlanta cyclists were cycling about twice as fast as the Delft cyclists. Although other factors such as typical trip lengths, cycling culture, and bike types could also influence the ideal speeds, the thematic analysis results coupled with the large speed differences suggest that cyclists' speed is influenced by pressure from the speed differentials in shared lanes. This may reveal the importance of infrastructure separating modes by speed, as the Dutch system does.

Pavement condition was the second most common stressor in Delft and third in Atlanta. Pavement condition, included in BLOS, has been considered in terms of physical comfort (*40–42*), but is infrequently considered in stress studies. The findings of this study suggest that this is a more important factor than previously acknowledged.

A more detailed analysis was performed on the components of the infrastructure theme. It was shown that presence of bicycle facilities is the most important aspect of the infrastructure to cyclist stress. This could explain why over double the percentage of participants in Delft who identified infrastructure as a stressor did so in Atlanta. This fits with previous findings that the presence of bicycle facilities is important to reducing cyclist stress. Sight distance caused some stress in both locations but was a substantial component of reducing stress via infrastructure in Delft. This could be related to the slower speeds in Delft allowing cyclists more time to react to visual cues. Width and presence of bicycle facilities are included in all the existing infrastructure ratings systems, but sight distance, mentioned more frequently than number of lanes, has yet to be considered.

The number of travel lanes had a nearly even percentage of participants mentioning it as a stress reducer (7%) and as a stressor (10%). It reduced stress because cyclists felt vehicles were more able to give sufficient space when passing if there were more lanes. This suggests that number of travel lanes alone may not be as simple of an inclusion to measures of cyclist stress. Instead, aspects such as speed (high speeds often associated with high lane numbers) and roadway width may be better indicators.

4.8 Conclusion

Previous studies have assessed stress, but variables collected to conduct the assessment have been largely defined by the researchers. In this study, participants self-identified their causes of stress through a near real-time interview. This study confirmed and at times emphasized some of what is already known, especially the importance of motor vehicle interaction to cyclist stress. This study also contradicted the idea that number of travel lanes is a key stressor, instead suggesting that it can serve as both a stressor and stress reducer and that other stressors may be more influential. In addition, this study also highlighted new insights into causes of stress. For example, pavement condition is often overlooked but came out in the top three stressors in this study. The interviews also allowed for a new perspective on speed and the identification of sight distance as a factor in stress. Finally, this study also looked at close-pass events and how attitudes impact stress during them. The results were not definitive but suggest that the Delft cyclists' comfort with closer passes could be associated with their belief that motorists notice them and/or the low speed of vehicles.

There were several limitations to this study. First, although for studies incorporating the use of instrumented bicycles and quasi-naturalistic cycling, the sample size was reasonable, the analysis would have been stronger with a larger sample size. Second, some of the study design was not as consistent as desirable including the difference in bicycles used and the variation in the familiarity question. Finally, it could be desirable to perform the study again in more comparable cities in terms of population and transportation infrastructure.

Findings indicate that a few themes relating to cyclist stress require further research. The results suggested that there may be some interaction between cyclist speed, stress, and their ability to foresee risky situations which warrants further study. The results about pavements also suggest that studies on pavement management for cyclists should also consider their stress, not just physical comfort. In addition, ambiance was mentioned by 14% of participants and a study specifically on ambiance could be used to aid in inexpensive improvements to the streetscape that could impact people's willingness to cycle.

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CHAPTER 5. THE INFLUENCE OF SITUATIONAL COMPLEXITY, STRESS, AND STATED SKILL ON CYCLISTS' GAZE BEHAVIOR

ABSTRACT

Much of the world has improved in terms of road safety, but cyclist injury and fatality rates have not decreased at the same rate as motorist and passenger injury and fatality rates. Gaze behavior has been extensively studied in driving due to its relevance to safety and vehicle control, but gaze behavior is only starting to be studied in cyclists. This exploratory study aims to begin filling this gap by using eye tracking glasses and quasi-naturalistic cycling to explore how situational complexity, stress, and stated skill influence gaze behavior. This study took place in Delft, The Netherlands with 8 female and 18 male participants, all affiliated with the university. Cyclists were asked to ride an instrumented bicycle for about 30 minutes on a route with minimal vehicle interaction at off-peak and peak hour. Cyclists filled out a survey about their cycling habits, attitudes, and skill level and were interviewed about their stress levels at three designated locations during/after the ride. Cyclists' horizontal and vertical gaze range, gaze area, and fixation number and duration were compared by segment. The segments were divided by complexity and stress and the riders by self-identified high motor-tactical skill and high safety motive ratings. The results suggest that the primary cycling task (maneuvering, scanning, etc.) or other factors dominate over complexity for these measures, but stress and stated skill do have influence on cyclists' gaze. The most striking results showed that the safety motives group utilized improved scanning behavior and a gaze more focused on the center of their view where most safety-critical cues appear. The measures used were effective in highlighting information about cyclists' scanning and gaze range. These results highlight some areas warranting future research including the influence of cyclist skill, experience, and stress on gaze behavior. They also serve as a building block to layer gaze behavior in mixed vehicle-cyclist situations.

5.1 Introduction

Due to its societal benefits, cycling is experiencing a resurgence in many countries around the world. However, even in established cycling countries, such as the Netherlands, the rate of cyclist injuries/deaths is not decreasing at the same rate as motorist injuries/deaths. Literature shows that most cycling accidents are caused by human error, more often by other road users than the cyclist (Simpson & Mineiro, 1992). The rate and severity of accidents can be reduced and mitigated by forgiving infrastructure design that assumes error will happen (Cushing, Hooshmand, Pomares, & Hotz, 2016). Although many safety treatments for cyclists still need more rigorous, systematic safety assessment, it's been shown that infrastructure choices such as building a bike lane consistently improve safety (DiGioia, Watkins, Xu, Rodgers, & Guensler, 2017; Mooney et al., 2018). Over time, a rich literature has been developed regarding general categories of infrastructure that are safer for or perceived as safer by cyclists (Harkey, Reinfurt, & Knuiman, 1998; Klobucar & Fricker, 2007; Landis, Vattikuti, & Brannick, 2007; Mekuria, Furth, & Nixon, 2012; Pikora, Giles-Corti, Bull, Jamrozik, & Donovan, 2003). Although perceived safety does not always match actual safety, infrastructure that is perceived as safer can increase cycling rates leading to more awareness of cyclists and the safety in numbers phenomenon (Cushing et al., 2016; Fyhri, Sundfør, Bjørnskau, & Laureshyn, 2017; Mooney et al., 2018).

As cyclists' safety is associated both with behavior (road user error) and infrastructure design, more detailed information about how cyclists interact with their surroundings can aid in developing more forgiving, safer designs for cyclists. Gaze behavior is one aspect of how road users interact with their surroundings and has been extensively studied in driving research due to its relationship to driver safety and vehicle control. However, to date, gaze behavior analysis has not been widely used in cycling research.

Although aspects of the driving experience, such as high speeds and the presence of the dashboard, are not applicable to cycling, driving studies of gaze behavior can serve as a starting point for measures and methods in cycling studies. Nunes & Recarte (2002) considered distraction from hands-free phone conversations. They looked at the cognitive demands of hands-free-phone conversations considering fixation duration, fixation location, and pupil size. They found that the more complex the task, the more tunnel vision occurred. Chapman, et al. found that more experienced drivers use more fixations of shorter duration than inexperienced drivers (Chapman, Underwood, & Roberts, 2002). They also showed that experienced drivers scan a wider frame of view (Chapman et al., 2002), while Mourant & Rockwell showed that experienced drivers tend to look at the right lane edge near the horizon (Mourant & Rockwell, 1970). These driving studies suggest that measures of gaze range in x and y and measures of fixation should be considered for cyclist gaze behavior. This is further supported by a review paper that concluded the most common gaze measures in driving studies included number and duration of fixations and exploration of areas of the visual frame (Kapitaniak, Walczak, Kosobudzki, Jóźwiak, & Bortkiewicz, 2015).

Although eye tracking has been infrequently used in naturalistic cycling, there have been studies that described cyclists' gaze behavior, especially in terms of bicycle control, distraction, and hazard perception. Vansteenkiste and his coauthors from Ghent University are the most prolific in the area of cyclist control of a bicycle (Vansteenkiste, Cardon, D'Hondt, Philippaerts, & Lenoir, 2013; Vansteenkiste, Van Hamme, et al., 2014). In addition to defining how cyclists maneuver their bicycle in a variety of situations, Vansteenkiste, Zeuwts, Cardon, Philippaerts, & Lenoir (2014) found that when biking on low quality roads, cyclists tended to look close to them rather than at further off environmental hazards.

Other studies have focused on cyclist distraction and hazard detection (Ahlstrom, Kircher, Thorslund, & Adell, 2016; Mantuano, Bernardi, & Rupi, 2017; Stelling-Konczak et al., 2018; van Paridon, Leivers, Robertson, & Timmis, 2019). Ahlstrom et al. (2016) focused on visual strategies employed when using a cell phone in traffic. They found that cyclists chose strategic moments to use their cell phone where they could glance at the phone for longer. Stelling-Konczak et al. (2018) studied glance behavior of teenage cyclists while using headphones. Although cyclists believe they compensate for the loss of audio signal by glancing more, it was found that there was no statistically significant difference in glance behavior when listening to music. Mantuano et al. (2017) found that along a cycle track that has potential for pedestrian-cyclist interaction, cyclists are inclined to watch pedestrians, even delaying observation of an upcoming intersection to watch them. Van Paridon et al. (van Paridon et al., 2019) studied young cyclists' hazard perception finding that children adjust their search strategies with intricacy of the situation and that the children spent longer looking at the pavement in sections of poor pavement. Rupi and Krizek studied cyclists' gaze behavior at intersections to find that their gaze patterns differ based on cyclists' experience with more experienced cyclists showing longer fixation durations and less gaze activity (Rupi & Krizek, 2019). A recent study, and the most similar to this research, looked at the effects of subjective risk and visual space on cyclists' gaze behavior(von Stülpnagel, 2020). They found that increased subjective risk which was associated with increased visual complexity resulted in what they call a “more hectic and cluttered gaze behavior” that included shorter fixations in directions diverging more from the lane of travel and on objects closer to the cyclist. Combined these studies emphasize the importance of other road users, pavement condition, subjective risk, and experience to cyclists’ gaze behavior.

The present study will build upon these findings on cyclists’ gaze behavior. None of these studies have attempted to understand how stress influences cyclists’ gaze behavior; however, cyclists’ stress is a major concern in design, planning, and research for cyclists (e.g. (Caviedes & Figliozzi, 2018; Furth, Mekuria, & Nixon, 2016; Geller, 2006; Heesch, Sahlqvist, & Garrard, 2012; Mekuria et al., 2012; Nuñez et al., 2018; Pikora et al., 2003). Stress has a very fluid definition with the most basic being “the non-specific response of the body to any demand for change”, indicating that it is a complex response comprising psychological, cognitive, and behavioral components (“What is Stress? - The American Institute of Stress,” 2019). This definition is ultimately highly context dependent.

In this study, stress will be defined by participants’ stated stress which the authors hypothesize is a combination of anticipation of future events, reactions to the immediate surroundings, and a cyclists’ confidence they can manage them. The causes of cyclists’ stress were previously explored using the survey data collected in this study, and showed that pavement, interactions with motor vehicles, and infrastructure most strongly influenced stress (Gadsby, Hagenzieker, & Watkins, 2021). These can be associated with what is immediately happening around the cyclist, but other causes of stress such as anticipation can be associated with the concern for future events. Stress levels, as reported by the study participants, and their influence on gaze behavior are explored in this study.

Stress may be influenced by two potential explanatory variables that build upon existing literature: maneuvering complexity (related to their immediate surroundings) and stated skill (related to their confidence). This study looks at skill as defined by the cyclists' themselves which is both an operationalization of actual skill, but also gives insight into the cyclists' confidence in that skill allowing them to manage situations that occur. Although this study was executed prior to their publishing, von Stülpnagel (von Stülpnagel, 2020) has already reported on the affects of visual complexity. But complexity of maneuvering may also influence the stress and gaze behavior of a cyclist as suggested by the influence of pavement condition on young and older cyclists (van Paridon et al., 2019; Vansteenkiste, Zeuwts, et al., 2014). Additionally, a cyclists' ability or confidence in their abilitiy to successfully maneuver and react to future stimuli may also influence their stress. The influence of experience on cyclists' gaze behavior has been studied, but this present study will use a more detailed survey on cyclists' stated skill to explore how their perspective on their abilities and the resulting gaze behavior aligns with previous studies of experience. Combined, this study will explore the influence of stress, an important component of cycling safety research, and two potential explantory variables within stress: complexity (of maneuvering) and stated skill. These address two of the three hypothesized components of stress: immediate surroundings and confidence.

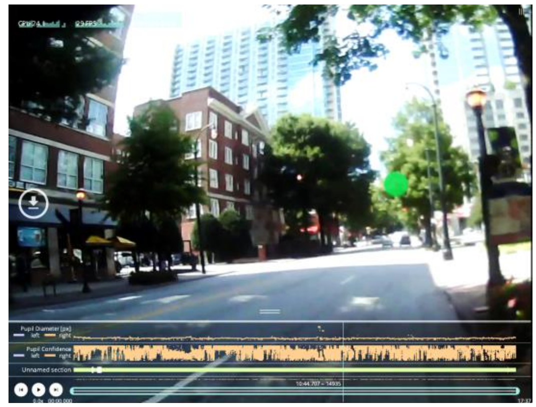
The aim of the present study is to use quasi-naturalistic cycling and eye tracking to explore how cyclists' gaze behavior is influenced stress and two potential components of stress: stated skill and complexity (of maneuverability) in the absence of heavy motor vehicle traffic. This study is exploratory in nature and presents initial findings on variations in cyclists' gaze behavior in real world cycling. This will provide a baseline to build upon for future understanding of cyclists' gaze behavior with the added complexity of motor vehicle-cyclist interaction which will add the third hypothesized component of stress: anticipation of future events. Furthermore, understanding of general cyclist gaze behavior in these situations may be useful in designing safer bicycle facilities.

5.2 Initial Eye Tracking Tests

Prior to starting data collection with the eye trackers, a feasibility test was performed in 2018. The initial results were presented at the International Cycling Safety Conference in October 2018. This initial study informed the study that is the subject of this chapter and supported the hypothesis that differences in skill, stress, or infrastructure may influence gaze behavior.

Data were collected in the Netherlands and the USA. Two participants, a comfortable, but cautious female cyclist and a strong, and fearless male cyclist, wore the glasses in the Netherlands. In Atlanta, a different pair of participants, one a comfortable, but cautious female cyclist and the other a strong and fearless male cyclist, wore the glasses. Both pairs rode on various types of infrastructure.

Only qualitative results were possible due to loss of data in the USA from sunlight, but some trends appeared. The confident cyclists tended to look above the horizon, suggesting they were looking further ahead, and scanned the scene with a sweeping gaze. The cautious cyclists tended to look below the horizon, closer to them, and scan with quick glances around the scene. Examples of these differences are shown in Figure 5-1. When the cautious cyclists were on very low-stress facilities, such as a park, their gaze tended to be similar to a confident cyclist's gaze. These results suggest that there are differences in gaze behavior between when a cyclist is more stressed as compared to less stressed. The cyclist's comfort with biking influences their baseline behavior, but so does skill. The more skilled cyclists were more likely to check doors of parked cars and scan at intersections.



(a-1) (a-2)

(b-1) (b-2)

Figure 5-1 a) shows the confident cyclist and b) the more timid cyclist. The 1 images are from The Netherlands and 2 from Atlanta

5.3 Methods

The objective of this study is to explore gaze behavior in the absence of significant motor vehicle interaction so that the gaze behavior could ultimately be separated and layered with that from motor vehicle interaction. Towards this end, the research team designed a short

(5 km) route around the Dutch city of Delft. Participants cycled the route during off peak and peak hours on an instrumented bicycle while wearing eye tracking glasses. The cyclists were also interviewed about their experience in the experiment; their cycling habits, attitudes, and skill; and their demographics.

5.3.1 Participants/Recruitment

The study had 28 participants, 26 (8 female) who rode both peak and off-peak and 2 (1 female) who rode only peak hour. Participants were recruited via email and fliers. Due to the recruitment methods and requirement to ride off-peak, all participants were affiliated with the Delft University of Technology (TU Delft) and most were students. 82% of participants were in the 25-34 age range. Nine participants were originally from the Netherlands, but all had some familiarity with cycling in the Netherlands and the chosen route. To increase participation as the study continued, the final 10 subjects were provided a 10-euro gift card incentive after their second ride.

5.3.2 Route

Delft is a small, historic city in the Netherlands with a population of approximately 100,000. The Netherlands has a bicycle modal share just over 25% (*24*). In Delft, the bicycle modal share is expected to be closer to 40% for trips between 1 and 7 kilometers, as is common in urbanized areas in the Netherlands (*25*). The route began at TU Delft, travelled through the historic center of Delft, and returned to TU Delft. It was approximately 5 km long and took approximately 25 minutes to cycle. The route was designed to incorporate a mix of infrastructure and land use types. Figure 5-2 shows a map of the route and the infrastructure.

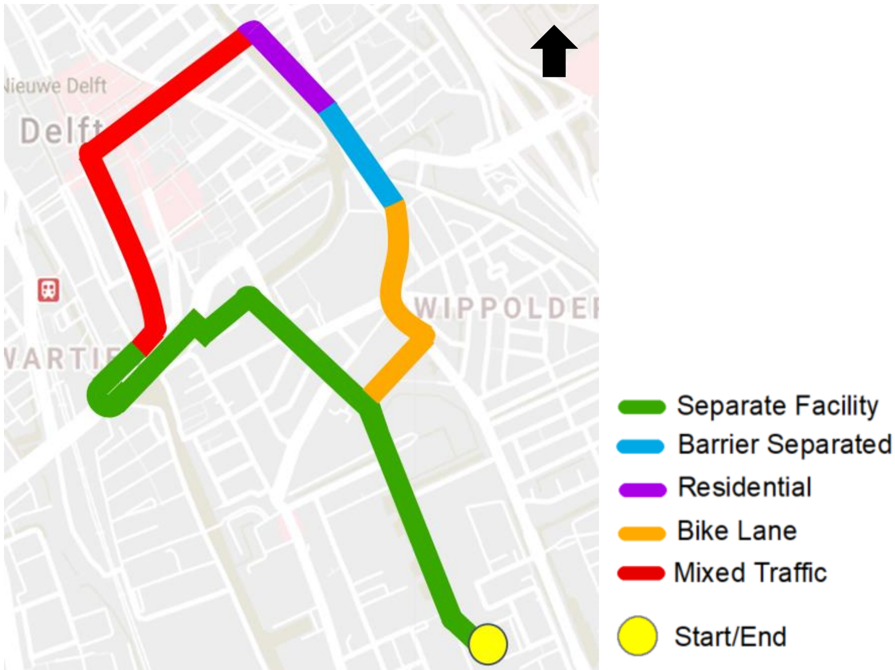


Figure 5-2 Route through Delft color-coded by infrastructure type

5.3.3 Sensors

An instrumented bicycle and eye trackers were used to monitor the cyclists in the study. The instrumented bicycle was a standard Dutch city bicycle with back pedal brakes. Choosing a standard bicycle meant most participants were familiar with the type of bicycle. The attached components sat on built-in bicycle racks and added just under 5 lbs to the bicycle. Participants could familiarize themselves with the bicycle prior to data collection to minimize influence from the type of bicycle and added components. The bicycle was equipped with front and back cameras, GPS, and LiDAR, as shown in Figure 5-3. The eye trackers were wearable Pupil Labs Core glasses, which were connected to a light laptop in a backpack worn by the rider.

The eye trackers produced two types of data. They provided a point gaze location for each frame resulting in 50 gaze points per second. Each location is given in normalized coordinates with (0,0) the bottom left of the frame and (1,1) the top right. Measures using this data will be referred to as measures of gaze. The eye trackers also produced information on groups of gaze points in the same area and labelled them a fixation. Fixations had associated locations and durations. Fixations can be challenging in this context because the cyclist is moving relative to the world. To adjust for this, the allowable dispersion of the gaze within a fixation was set to 4.5 degrees and the minimum duration to 150 ms. This adjustment allows for creating meaning from the fixation data but is imperfect. Therefore, differences in measures of fixations between groups will need to be more significant than the gaze measures. The eye trackers did not have an accelerometer or gyroscope on them. Through visual inspection of the video footage, the amount of time a participants' head was turned during data used in the analysis was minimized.

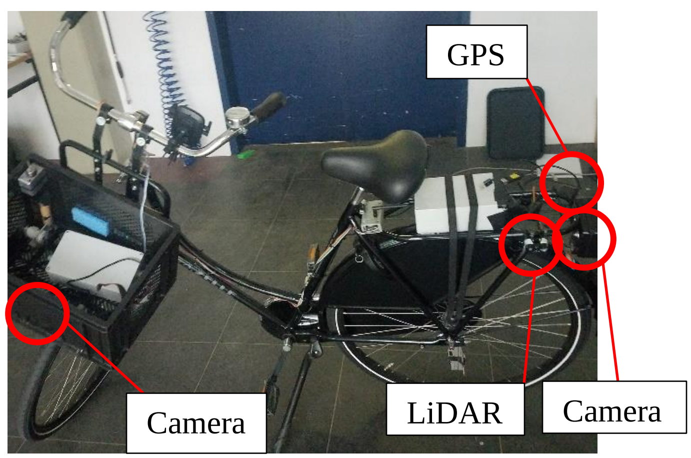


Figure 5-3 The TU Delft instrumented bicycle

The eye trackers were wearable Pupil Labs Core glasses. Table 5-1 provides the glasses specifications. The glasses were connected to a light laptop in a backpack worn by the rider.

Table 5-1 Eye Tracking Glasses Specifications

Specification	Value
Gaze Accuracy	0.60 degrees
Gaze Precision	0.08 degrees
Pupil Tracking Technology	Dark pupil
Sampling Frequency (Eye)	200 Hz
Sampling Frequency (World)	Variable 30-120 Hz depending on light levels

5.3.4 Survey Instrument

In addition to the sensors, three survey instruments were used: a pre-ride survey, mid-ride surveys, and a post-ride interview. The pre-ride survey included questions about the participant's cycling habits (i.e. frequency, primary mode of transportation), attitudes, skill (from the Cycling Skill Inventory (*26*)), and demographics. At two designated locations along the ride, cyclists stopped to fill in a map of the route based on their stress levels (low, moderately low, moderately high, high). After the ride, cyclists were interviewed to understand their reasoning behind their ratings for each segment, their familiarity with the route, and the influence of their accident history on their ratings. The cyclists' survey data were linked to their eye tracking data by a unique identifier given for each ride.

5.3.5 Protocol

Prior to the ride, the weather was checked to confirm that the likelihood of rain was small during the study. The study began with participants signing consent forms as approved by the human subjects research boards at both TU Delft and Georgia Tech. They were briefed on the experiment and asked to fill in the pre-ride survey. Once complete, the bicycle was sized to them, and they were equipped with the sensors. Then the participant began the ride with the researcher behind. They were instructed to cycle as they would normally as if the researcher was not present. The researcher was there to give directions as needed to limit wayfinding concerns so as not to impact their gaze patterns. In addition, the researcher could act in case of an emergency and manage equipment if needed although this was never necessary. The participant was asked to stop twice at designated locations to fill in the map survey. Once the ride was over, the sensors were removed, and the participant completed their map. The researcher then conducted the post-ride interview.

5.3.6 Analysis Methods

The first step of the analysis was to define and slice the three groupings of data: complexity, stress, and stated skill. All data slices were 5-10 seconds based on review of the situation to ensure approximately similar start/stop of the slice for each rider and consistent conditions within the slice. The sliced data provided information on the location in normalized coordinates (bottom left corner as (0,0), top right as (1,1)) of the gaze and fixations. These were run through a python code developed in house to output measures of gaze distribution and fixation duration. Gaze data below 70% confidence, as reported by the Pupil Labs software, was removed.

5.3.6.1 Data Grouping and Slicing

For this analysis, complex situations required the cyclist to change speed as derived from speedometer and video data. In total, the complex segments taken from every cyclist's eye tracking data included a small barrier that cyclists had to pass through, as well as a narrow, blind curved segment around construction, an unsignalized crossing and left turn, and two bumpy roads. As controls, two segments that showed no speed change were taken for each cyclist, one on a smooth, two-way cycle track through TU Delft's campus and another on a smooth, two-way cycle track along a canal. Each of the complex situations were treated individually as their level of complexity and associated visual tasks varied. All seven segments were sliced for every ride and are shown in Figure 5-4.

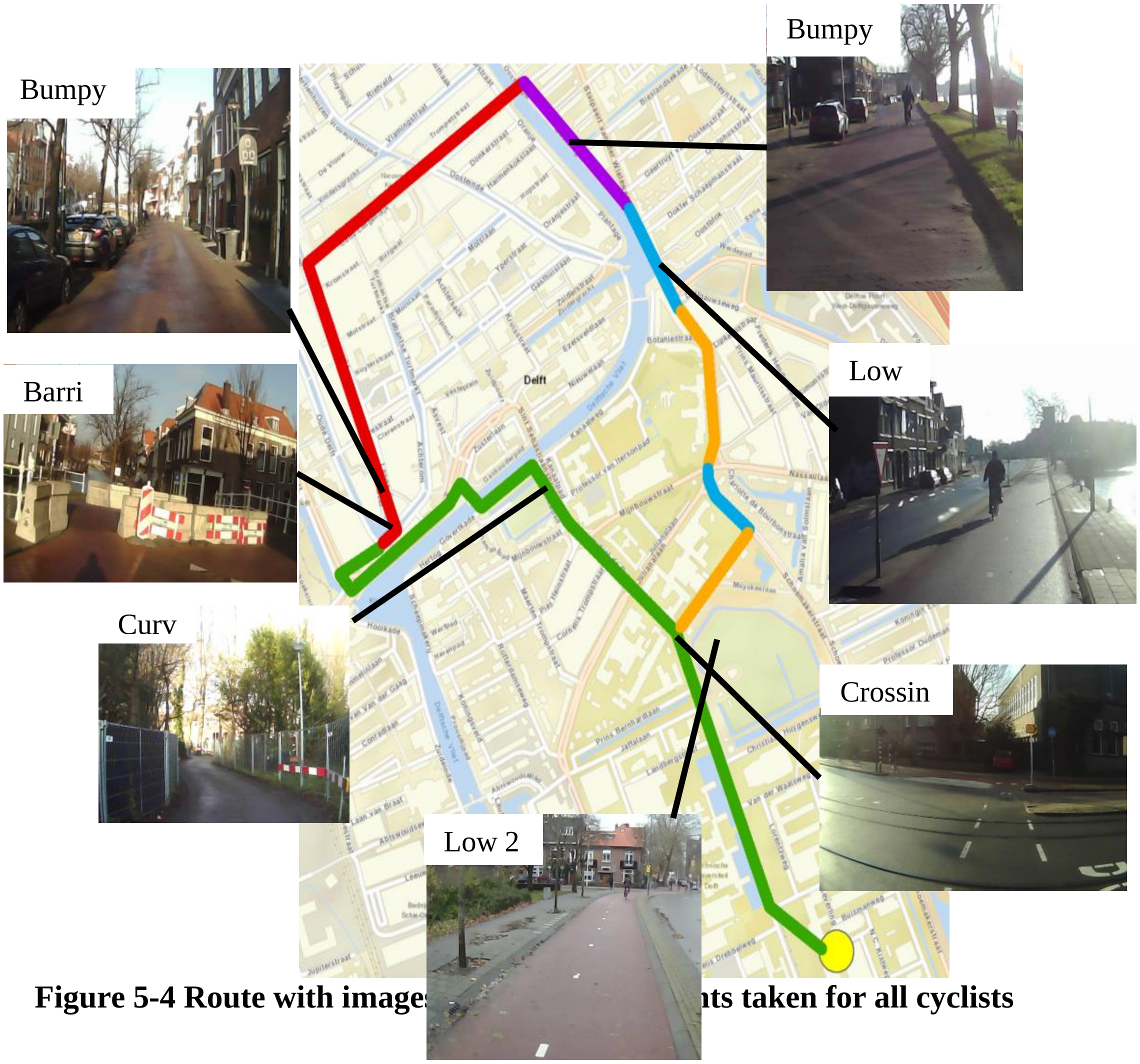


Figure 5-4 Route with image nts taken for all cyclists

In addition to slicing the data for complexity, situations that caused a rating above low stress for any rider were additionally sliced for the analysis on stress. These were identified based on the locations in the participants' stress maps marked as above low stress and the description of the stressor. The cyclists' videos were reviewed in these locations for a situation best matching the description. Situations that occurred in less than 5 seconds or that could not clearly be identified based on the location and description, were not used. Only the seven segments selected for the complexity analysis were sliced for every cyclist and these higher stress slices were added on an individual basis. If a cyclist had a stressful interaction with another cyclist and marked that as moderately high stress on their map, that moment would be sliced from their data only and added to the moderately high group. The complexity identifier (i.e. barrier, bumpy 1, etc.) was ignored for the stress grouping and each sliced video was identified by the affiliated stress rating. For example, some cyclists' trips through the barrier would be in the low stress group, some in the moderately low, and some in the moderately high. There was only one situation labelled high stress, so it was joined with the moderately high group.

The third category of analysis, stated skill, was defined by participants' responses to the Cycling Skill Inventory. The Cycling Skill Inventory asks participants to rate themselves on 17 Likert-scale items from definitely weak to definitely strong (*26*). The cited study observed that two components underlie the data: motor-tactical skills and safety motives. De Winter et al. (*26*) identified the questions tied to each component, and we used those to separate participants in this study. For safety motives these were: "obeying traffic signals", "avoiding unnecessary risks," "cycling carefully," "obeying traffic rules," and "showing consideration for other road users." For motor-tactical skills the responses were higher for: "cycling when it is slippery," "knowing how to act in particular traffic situations," "controlling the bicycle," "sudden braking and/or swerving when needed," "fast reactions," "predicting traffic situations ahead," and "maneuvering smoothly through busy traffic." The remaining questions represented a combination of the two skills.

Most participants in the current study rated themselves evenly among the two, but nine participants (16 total rides) in this study scored low in one category and high in the other. This was defined by a one point or greater difference between their average rating for safety motives and motor-tactical skills. Four scored higher for motor-tactical skills and five for safety motives. The remaining 19 participants scored less than one point different in the two categories and were group together in the "mixed" category as a baseline to compare to. The three groups of data for this analysis consisted of all rides by the four cyclists in the motor-tactical skills group, all rides by the five cyclists in the safety motives group, and all rides for the remaining 19 participants.

5.3.6.2 Measure Selection

In selecting measures to use, a wide variety of measures from the literature were considered. The intention was to select measures that could more generally describe cyclists' gaze as the complexity/task varied (traversing a barrier, cycling straight on smooth pavement, and making a left turn are all distinct tasks). Initially, pupillometry, fixation number and duration, median x and y gaze position, and areas of interest for both gaze and fixations were included. Pupillometry was too sensitive to variations in light levels and was removed from consideration early on.

To date, areas of interest are the most common way studies of eye tracking in cycling have measured gaze (*14*, *17*, *18*, *27*, *28*). Studies using areas of interest typically investigate a specific scenario or scenarios for observation of a particular object (e.g. (*28*)) or a particular action, such as right glances at intersections (*17*). Others look for a specific area, such as an area around the location where the path meets the horizon (*18*) or within the bike lane (*14*). Overall, using areas of interest means the researchers are looking for gaze to fall within or outside of a specific area. The use of areas of interest was not well suited for three reasons: the tasks for each slice changed; there was no specific gaze pattern we were looking for; and we wanted more generalized measures. Furthermore, using this technique becomes increasingly challenging with larger participant numbers as the area of interest often needs to be defined frame by frame (*14*, *18*). With 28 participants and 54 rides in total, this study had a sizeable data set. Following this more exploratory study, areas of interest may be used for future research on very specific gaze patterns.

Although we did not do frame-by-frame areas of interest analysis, we did calculate percentage of gaze in the four quadrants of the viewing frame, within a box centered at the nexus of the horizon and bike lane, within the bike lane, and above the horizon. The box centered at the nexus of the horizon and bike lane was designed to measure narrowing of gaze range. However, we discovered that the assumption that narrowing of gaze range would occur in the center box was not necessarily correct after reviewing the data. This was ultimately replaced by a measure of gaze area that was defined by the area of a rectangle with a base defined as the width of the horizontal gaze range and the height defined as the vertical gaze range. The analyses of above the horizon and within the bike lane did not show strong results even in the descriptive statistics, so are not presented here. The measures of the spread and median of gaze positions in the horizontal and vertical planes were kept.

After extensive exploration and consideration, the final measures selected were x (horizontal) and y (vertical) range, median x and y positions, number of fixations/second, and fixation duration.

5.3.6.3 Data Analyses

Boxplots and heatmaps were created by compiling all x and y coordinates of the gaze for each group (i.e. every data slice for "barrier" combined to one full "barrier" dataset or every data slice marked as "moderately low stress" combined to one full "moderately low" dataset). These were created using the Python programming language to act as visual representations of the data in both 1D and 2D. They are visually compared in the results section.

All measures mentioned in the previous section were calculated per ride then averaged by group. For example, the x gaze range was calculated for each "barrier" data slice, then the average of all x gaze range values for "barrier" data slices was taken for the descriptive statistics. Initially, the same aggregation technique used to make the boxplots and heatmaps was going to be used for the measures. However, the x and y range and gaze area needed to be calculated for each sliced data file and averaged because when using the initially aggregated dataset, all range values came out to the maximum possible area of 1. Calculating the other measures this way did not alter the results and improved clarity for the statistical analyses, so it was decided that all measures would use the same aggregation technique.

Descriptive statistics and statistical testing were used to explore the results. Because of the exploratory nature of the study, we would like to emphasize that the statistical analyses serve to gain insights into differences between the groups but were not intended to test specific hypotheses. The non-parametric Kruskal-Wallis test was used to statistically compare all measures. Kruskal-Wallis tests were chosen because it is useful for testing whether there is a difference among more than two groups, but not beholden to the assumptions of a one-way ANOVA. In this way, each segment, stress level, and skill could be treated individually to identify if any had a statistically significant deviation. To identify specific differences, Mann-Whitney post-hoc tests were performed. Results for the post-hoc tests for statistically significant results can be found in Appendix D. PostHoc Tests for Chapter 5

Each measure calculated for each slice of data was labelled with its corresponding group for skill, segment type, and stress level. These labels were used to statistically compare the measures using the R programming language. For stated skill (Results Section 3.1), groups were chosen as the cyclists in the high motor-tactical skill group, the high safety motive group, and the remaining cyclists who had approximately even scores in the two categories. For the complexity analysis (Results Section 3.2), the groups were the data for all rides at each segment. For stated stress (Results Section 3.3), the groups were defined by the stress rating given to each slice, so all the sliced data rated as low, moderately low, and moderately high were each a group. The groups within each analysis were mutually exclusive. A summary of the aggregation techniques, measures, and analyses is provided in Table 5-2.

Table 5-2 Summary of measures and analyses using each aggregation technique

Aggregation Technique	Measures	Analyses
Raw data (x,y gaze positions) combined by group (i.e. all x,y gaze positions for the barrier segment)	None	Boxplots, Heatmaps
Raw data was not combined with other data slices, each measure was calculated for each slice, then measures were grouped (i.e. by segment) for the analyses	Median x position, Median y position, Mean Fixation duration, Mean X range, Mean y range, Mean gaze area, Mean fixations/second	Descriptive Statistics, Kruskal-Wallis Statistical Tests, Mann Whitney Post-hoc test

5.4 Results

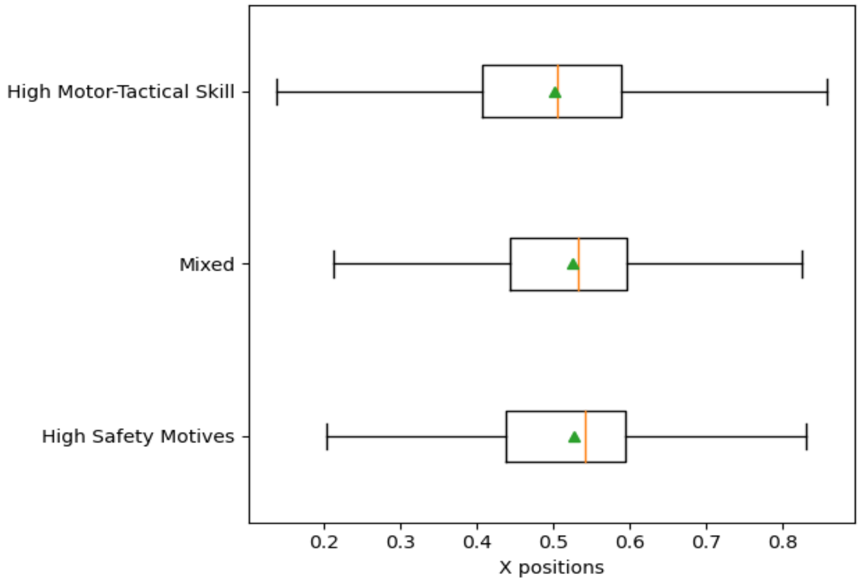
The gaze behavior measures were compared across multiple dimensions: stated skill, complexity of the segment, and stated stress. The gaze distributions are presented visually as box-and-whisker plots and numerically in the following tables. Heatmaps of the gaze distribution of the stated skill group by complexity segment are also presented to further explore findings.

5.4.1 Stated Skill

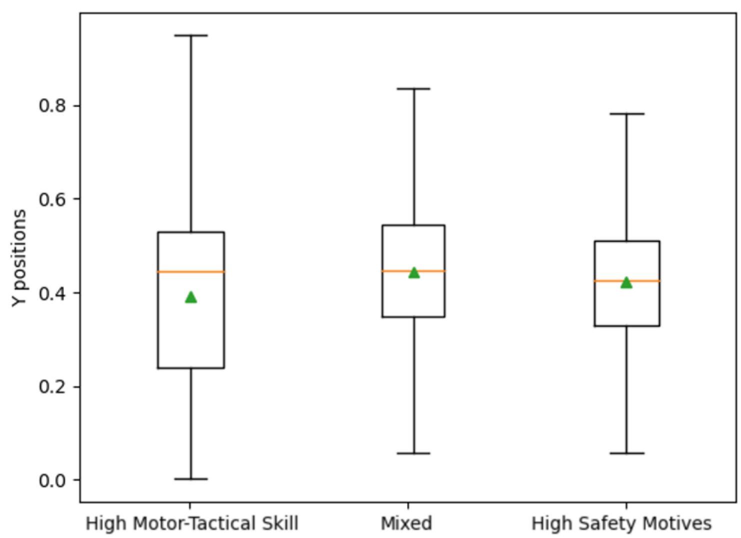
As mentioned in the Methods section, 5 people rated their safety motives notably higher than their motor skills and 4 participants rated their motor-tactical skills notably higher than their safety. Their gaze patterns are compared here along with the remaining 19 participants, labelled “mixed”.

Figure 5-5 displays the x and y positions as boxplots and Table 5-3 presents the numerical results and statistical significance. Although the medians are similar, both the box and whiskers of the high safety motive participants are much shorter than the motor-tactical skills group, suggesting that there is reduced variability in the gaze. However, when looking at the mean x and y range in Table 5-3, the high safety motive group has a wider x and y range. This resulted in a highly significant effect on x-range, but not on y-range. The combination of x and y range showed that the cyclists in the high safety motive group exhibited a larger gaze area which differed significantly from those in the high motor-tactical skill group. This suggests that cyclists with a higher safety motive, but lower motor-tactical skill ratings tend to scan more frequently than cyclists with a similar or higher motor-tactical skill score.

The number of fixations/second was lowest for the high motor-tactical skill group and highest for the high safety motive group which was statistically significant. Although not significant, it is notable that the high motor-tactical skill group also showed the shortest fixation durations and the safety motive group the longest.



(a)



(b)

Figure 5-5 (a) x position by CSI, (0.5 as center), (b) y position by CSI (0.5 as center), the line represents the median and the triangle the mean

Table 5-3 Numerical gaze measures by stated skill with standard deviation in brackets and Kruskal Wallis Test Results (* p<0.05; ** p< 0.01 ; *** p < 0.001)

	MEDIAN X POSITION	MEAN X-RANGE***	MEDIAN Y POSITION	MEAN Y-RANGE	MEAN GAZE AREA**	MEAN NUMBER OF FIXATIONS/ SECOND**	FIXATION DURATION (MS)
HIGH MOTOR-TACTICAL SKILL	0.53 (0.13)	0.60 (0.32)	0.44 (0.19)	0.50 (0.20)	0.23 (0.16)	1.8(1.5)	264 (335)
MID/MID	0.52 (0.12)	0.69 (0.22)	0.44 (0.12)	0.53 (0.21)	0.30 (0.18)	2.0(1.4)	285 (387)
HIGH SAFETY MOTIVE	0.54 (0.12)	0.72 (0.15)	0.42 (0.14)	0.63 (0.17)	0.33 (0.17)	2.6(1.4)	294 (295)
HIGH/HIGH	0.55 (0.12)	0.70 (0.19)	0.47 (0.16)	0.58(0.19)	0.30 (0.18)	2.8(1.1)	278(373)
K-W TEST RESULTS	X^2_2=1.56, *p*=.450 ε^2=0.001	X^2_3=108.1, *p*<.001 ε^2=0.004	X^2_2=0.38, *p*=.820 ε^2=0.030	X^2_3=16.36, *p*<.001 ε^2=0.003	X^2_2=11.46, *p*=.003 ε^2=0.027	X^2_2=11.59, *p*=.003 ε^2=0.023	X^2_2=1.37, *p*=.505 ε^2=0.002

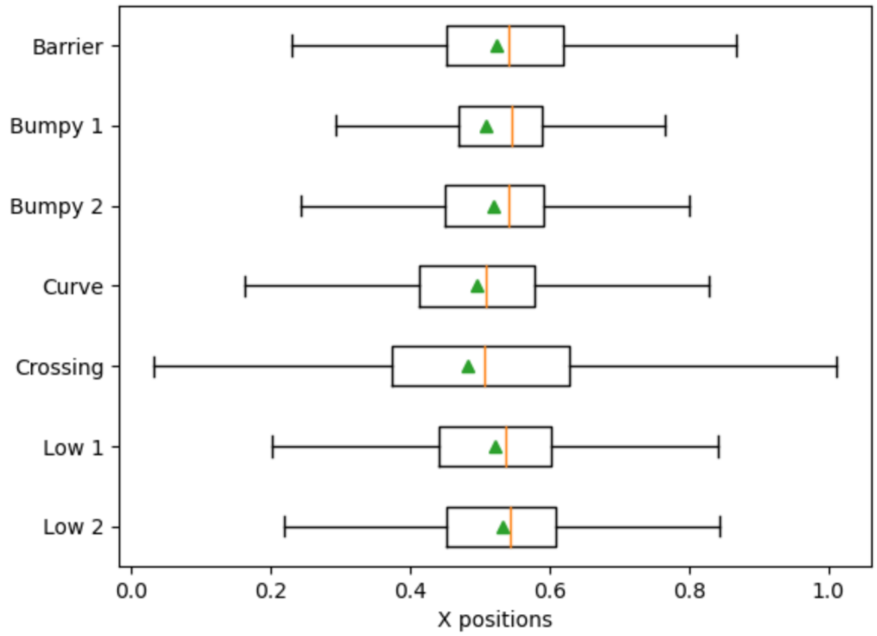
5.4.2 Complexity

The segments chosen included five more complex segments (a barrier, a narrow curve, two bumpy sections, a crossing), and two control segments. The segments are treated individually and vary in complexity. The x positions of the gaze in normalized coordinates by segment are shown in Figure 5-5a and the y positions in Figure 5-6b. Table 5-4 contains gaze measures and their significance. Figure 5-6a does not show great variation based on the complexity of the segment, and there was not a significant effect of complexity on either the median x position or the mean x-range.

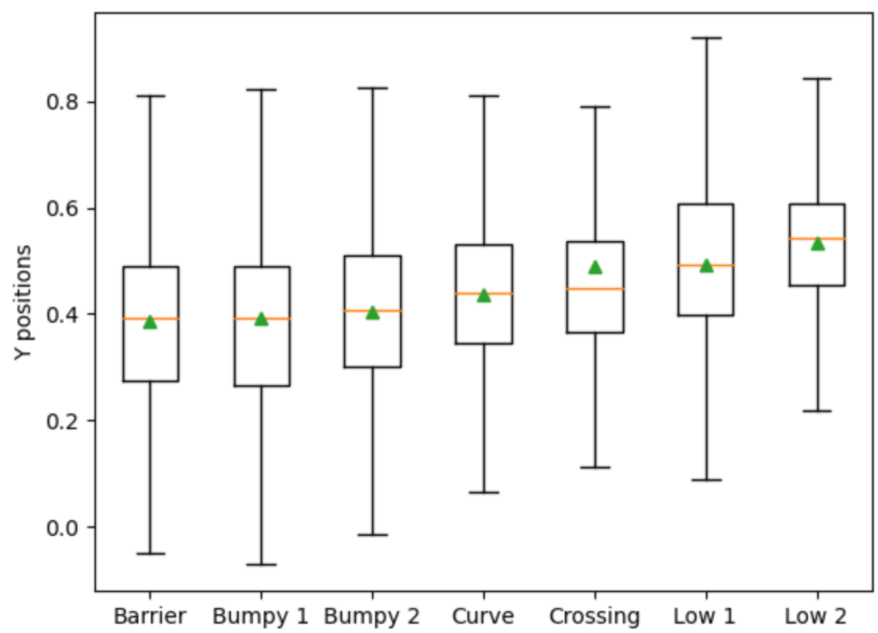
As can be seen in Figure 5-6b, the low complexity segments have a higher positioned gaze than the higher complexity segments. The bumpy pavements and the barrier have the lowest gaze, which could be related to their bicycle control related tasks. These differences did not result in a significant effect, but there was a significant effect on y-range and a highly significant effect on gaze area. The biggest difference was between the curve and the barrier which could be related to differences in scanning and focused bicycle-control tasks.

Although the fixation measures did not show a significant effect, they are still interesting for this exploratory study. The mean number of fixations/second was highest for the barrier section, and it had a relatively lower fixation duration. Additionally, the fixations were longer lasting for the two low complexity sections although they showed similar fixations/second to the other segments.

It is also notable that the two low complexity segments are most similar to each other and the two bumpy pavement sections are most similar to each other. This is most clear in the boxplots and the measures for the fixation durations and the median y position.



(a)



(b)

Figure 5-6 (a) x positions by segment (0.5 as center), (b) y position by segment (0.5 as center)

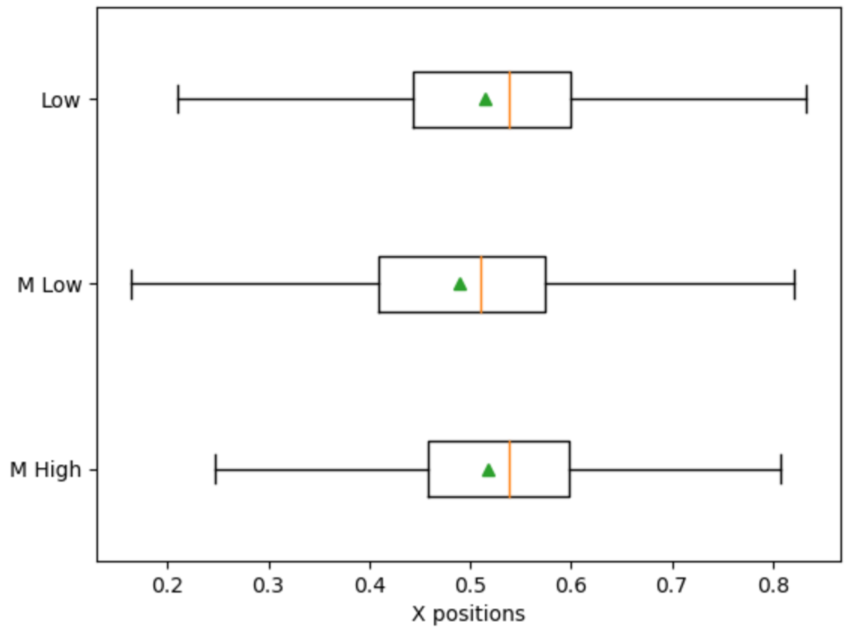
Table 5-4 Numerical measures of gaze behavior by segment with standard deviation in brackets and Kruskal Wallis Test Results (* p<0.05; ** p< 0.01 ; *** p < 0.001)

SEGMENT	MEDIAN X POSITION	MEAN X-RANGE	MEDIAN Y POSITION	MEAN Y-RANGE*	MEAN GAZE AREA***	MEAN NUMBER OF FIXATIONS/ SECOND	MEAN FIXATION DURATION (MS)
BARRIER	0.54 (0.12)	0.64 (0.26)	0.39 (0.15)	0.47 (0.26)	0.20 (0.12)	2.8 (1.5)	255 (375)
BUMPY 1	0.55 (0.10)	0.66 (0.31)	0.40 (0.16)	0.54 (0.23)	0.23 (0.17)	2.1 (1.6)	283 (429)
BUMPY 2	0.54 (0.11)	0.73 (0.29)	0.41 (0.16)	0.62 (0.23)	0.32 (0.16)	2.3 (1.2)	286 (389)
CURVE	0.51 (0.19)	0.73 (0.25)	0.44 (0.14)	0.63 (0.20)	0.32 (0.19)	2.1 (1.4)	205 (192)
CROSSING	0.51 (0.11)	0.70 (0.27)	0.45 (0.15)	0.55 (0.25)	0.43 (0.17)	2.3 (1.3)	292 (341)
LOW 1	0.54 (0.12)	0.66 (0.28)	0.53 (0.15)	0.58 (0.20)	0.32 (0.18)	2.2 (1.2)	317 (308)
LOW 2	0.55 (0.11)	0.68 (0.26)	0.54 (0.14)	0.58 (0.19)	0.27 (0.15)	2.2 (1.4)	314 (371)
K-W TEST	X^2_6=5.35 p=.500 ε^2=0.002	X^2_6=11.95 p=.063 ε^2=0.017	X^2_6=10.36 p=.110 ε^2=0.013	X^2_6=15.57 p=.016 ε^2=0.028	X^2_6=30.81, p<.001 ε^2=0.072	X^2_6=1.72, p=.943 ε^2=0.012	X^2_6=5.09, p=.532 ε^2=0.0026

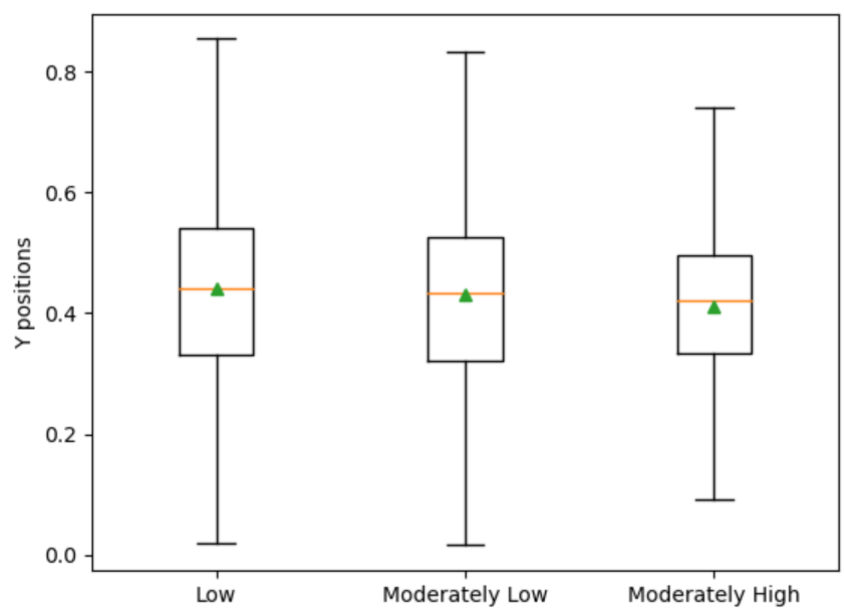
5.4.3 Stated Stress

The segments were rated and subsequently segmented based on the cyclists' stress levels. Additional segments were identified due to a stress rating of moderate or high. Unfortunately, only one segment was rated high stress, so the highest stress rating used in this study is moderately high.

Figure 5-7 displays boxplots of the x and y positions by stress levels and Table 5-5 displays numerical measures of the gaze. There was not a significant effect of stress on any of the measures used in this study, but that could be related to the relatively low stress of the route/location. This study was exploratory in nature and variations in gaze may be worth considering even if not statistically significant in this data set. Visually from the boxplots, the moderately high stress segments have a slightly narrower range of gaze in the x direction and y direction. The mean y-range consistently decreases with increasing stress and the mean x range decreased as well, although not consistently. Notably, the variation in gaze area decreased from the low to moderately high stress segments and the gaze area decreased slightly as well. This suggests that higher stressed individuals had a consistently narrower gaze area than lower stressed participants.



(a)



(b)

Figure 5-7 (a) x positions by stress rating (0.5 as center), (b) y position by stress rating (0.5 as center)

Table 5-5 Numerical gaze measures by stress with standard deviation in brackets and Kruskal Wallis Test Results (* p<0.05; ** p< 0.01 ; *** p < 0.001)

STRESS	MEDIAN X POSITION	MEAN X-RANGE	MEDIAN Y POSITION	MEAN Y-RANGE	MEAN GAZE AREA	NUMBER OF FIXATIONS / SECOND	FIXATION DURATION (MS)
LOW	0.54 (0.12)	0.69 (0.27)	0.44 (0.16)	0.57 (0.22)	0.30 (0.17)	2.3 (1.4)	282 (344)
MODERATELY LOW	0.51 (0.11)	0.65 (0.29)	0.43 (0.15)	0.50 (0.21)	0.29 (0.18)	2.2 (1.3)	264 (240)
MODERATELY HIGH	0.54 (0.13)	0.66 (0.34)	0.42 (0.13)	0.49 (0.28)	0.28 (0.05)	2.3 (1.4)	301 (568)
K-W TEST	X^2_2=4.85, *p*=.089 ε^2=0.007	X^2_2=5.03 *p*=.081 ε^2=0.008	X^2_2=0.65, *p*=.724 ε^2=0.003	X^2_2=4.01 *p*=.135 ε^2=0.028	X^2_2=0.93 *p*=.629 ε^2=0.003	X^2_2=3.59 *p*=.166 ε^2=0.004	X^2_2=2.04, *p*=.360 ε^2=0.001

5.4.4 Heatmaps

The heatmaps of all riders' gaze locations are shown in Figure 5-8. The two low complexity segments show a more central gaze. The two bumpy segments have more oblong areas of gaze extending from the lower right to upper left. The barrier segment which was the most challenging to maneuver shows the narrowest gaze distribution and the crossing where scanning was critical shows the largest.

Additional heatmaps shown in Figure 5-9 were created to further explore the two groupings (high safety motives and high motor tactical skills) for each of the complexity heatmaps in Figure 5-8. Figure 5-9 by separating the gaze patterns of each complexity segment by skill group allows us to explore the finding from Section 3.1 Stated Skill that within the boxplots, the high motor-tactical skill group had a wider gaze distribution than the safety motive group but a smaller gaze area in the calculations.

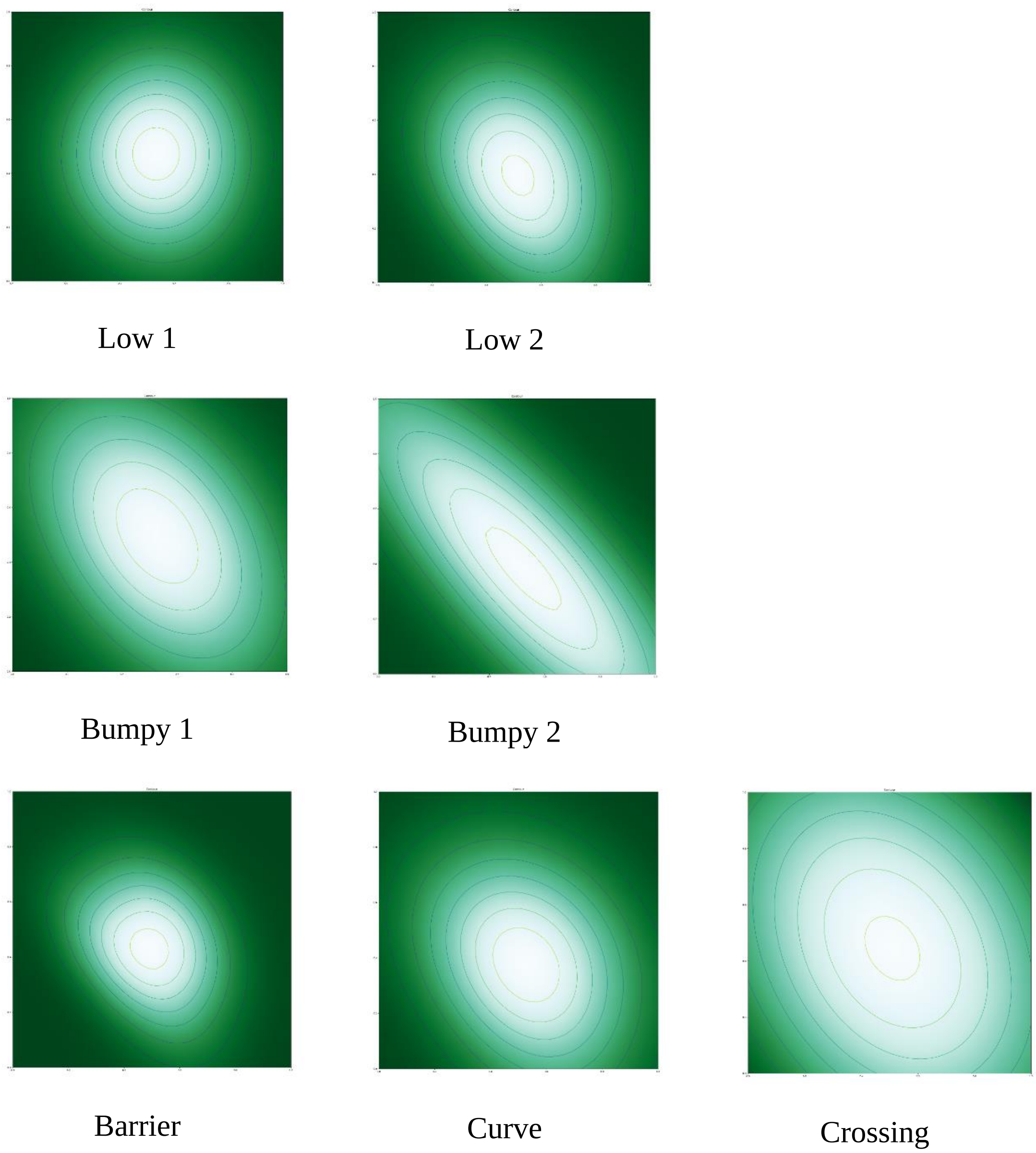


Figure 5-8 Heatmaps by segment, all maps cover the same area of normalized coordinates (0,0 – 1,1)

For conciseness, the 5 segments of higher complexity were included in Figure 5-9 as they were the most interesting. The heatmaps support the findings from the Stated Skill section.

The high safety motive group tended to have a much more centrally focused gaze with all members of the group tending to focus on a small area of the viewing frame. The gaze tended to be slightly right of center which fits with literature showing that we track the right side of the lane. In most cases the high motor-tactical skill group showed a wider gaze distribution than the combination of all rides. Their gaze distribution also tends to be more oblong with more time spent at opposing corners. This suggests that perhaps due to their high rated skills but low investment in safety motives, they spend more of their time looking at components of their view that are outside the immediately relevant area. Due to their self-rated low safety motives, these are unlikely to be safety-relevant gazes. This supports the findings in Section 3.1 Stated Skill and that the use of both aggregate gaze points used in the box plots and the individually calculated and aggregated measures such as the mean gaze area measure are useful in combination to study cyclists' gaze behavior.

Segmen t	All Rides	High Motor-Tactical Skills	High Safety motives
Bumpy 1			
Bumpy 2			
Barrier			
Curve			
Crossin g			

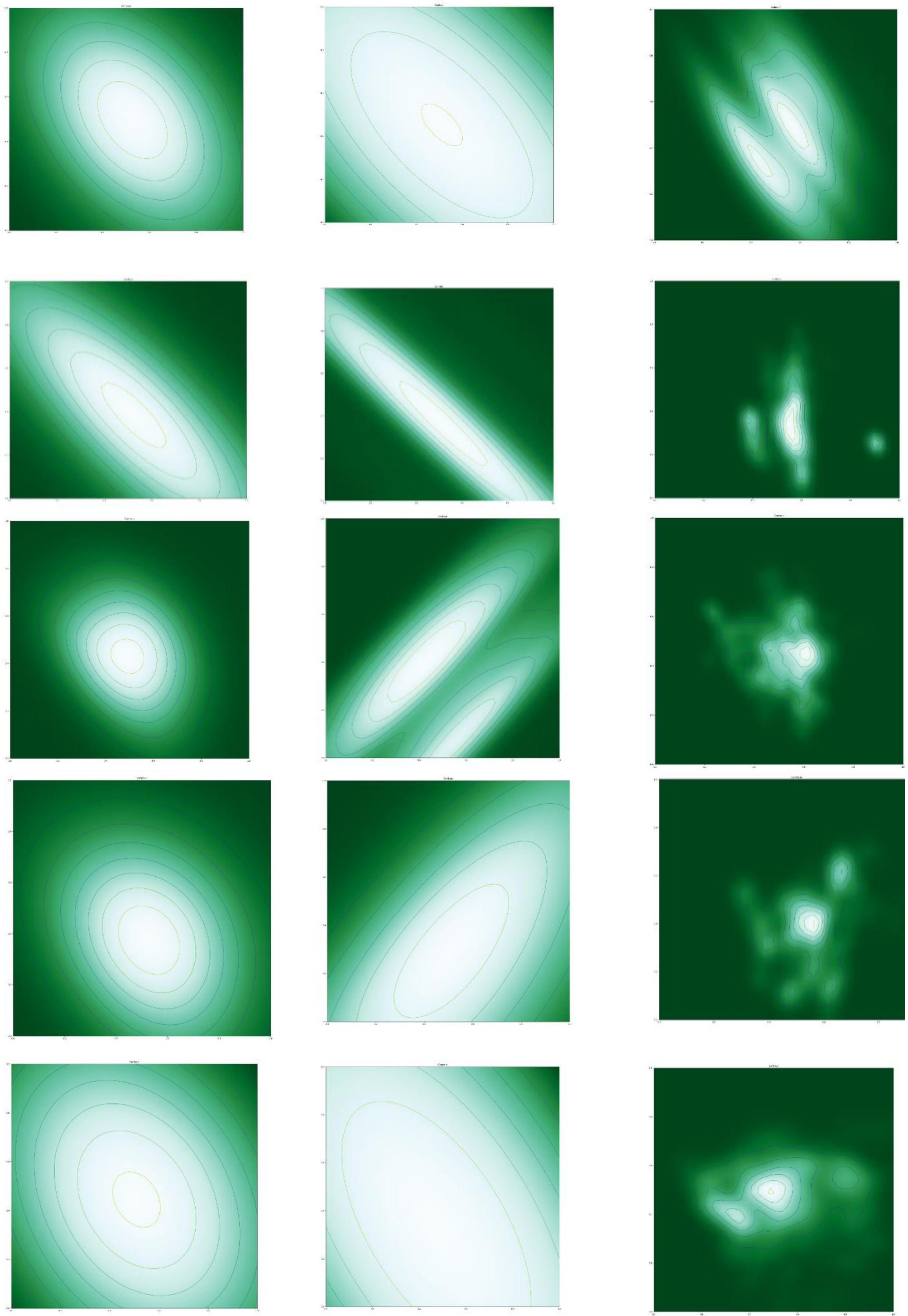


Figure 5-9 Heatmaps by segment and stated skill, all maps cover the same area of normalized coordinates (0,0 – 1,1)

5.5 Discussion

The results presented here are an exploratory foray into understanding cyclists' gaze behavior. Although many of the differences presented did not reach statistical significance, possibly due to variations in visual strategy between participants, the trends in the descriptive statistics align with findings in driver gaze behavior studies.

The most striking results suggest that skill, at least stated skill, influences gaze behavior. With improved bicycle handling/motor-tactical skills, both number of fixations and fixation duration decreased. Both horizontal and vertical gaze range was lower than for high safety motive cyclists. These results show mixed agreement with Chapman et al. (*7*), who found that drivers fixated more often, but for a shorter time and had increased horizontal gaze range after driver training. The cause of this mix may be attributable to what skill each group is demonstrating. It makes sense that the high safety motive cyclists would engage in superior scanning behaviors, but perhaps not exhibit the shorter-duration fixations that may be more closely tied to control skill and experience. In contrast, the high motor-tactical skill cyclists rated themselves low for safety motives, so it would make sense they would exhibit superior unconsciously controlled skill indicators for gaze (fixation duration) but engage in less scanning. The boxplots showed a wider variation in gaze from the high motor-tactical skill cyclists when combining their x and y gaze positions, but when averaging gaze range across segment/ride, the high safety motive cyclists displayed superior gaze range. This suggests that the high motor-tactical cyclists tended to look in a small area of the frame, but that small area was in a wider section of the frame across rides. This could mean the high motor-tactical skill cyclists were forgoing safety-related gaze to put attention on happenings around them (i.e. something happening across the street, birds flying, a nice view, etc.). The heatmaps displayed in section 3.4 further supported this explanation.

Based on driver gaze behavior literature, complexity would be assumed to reduce gaze area. The studies that found that complexity leads to decreased visual range often increased complexity by increasing difficulty of non-driving related tasks, such as talking on the phone (*6*, *29*, *30*). However, these non-driving tasks do not require the drivers' visual attention, and thus, do not conflict with driving-task necessary gaze behavior.

The results showed little significance for complexity as measured by need to reduce speed. The two bumpy segments and two low complexity segments had similar gaze patterns to their twin, suggesting that the primary visual task may be more important than general complexity as defined by a need to decrease speed. The primary visual task would be the required gaze patterns to navigate and maintain control of the bicycle. For example, the primary visual task for the crossing would be to scan to identify vehicles/other road users to determine if it is safe to cross or for a bumpy pavement to watch the bumps to navigate to not lose control of the bicycle. Because the two pairs of segments with the same tasks showed similar results, it appears that the primary visual task is more important the generalized complexity as defined by a requirement to change speed. The results suggest that gaze measures, at least the ones used here, cannot measure a difference based on complexity with varying primary visual tasks. Future studies should keep the primary visual task constant while varying complexity by other means.

Although complexity in this study did not show much statistically significant variation, this analysis did show that complexity may influence the height, and likely the distance ahead, the cyclist is looking with both low complexity sections showing a higher gaze pattern. Also influencing this, cyclists tend to look lower when the pavement is rougher. This was found by Vansteenkiste, Zeuwts, et al. (*15*), and replicated here with both bumpy sections showing some of the lowest gazes. This suggests that maintenance of bicycle facilities should be prioritized to create smoother pavements that lead to gaze behavior that is higher, more distant, and thus more capable to anticipate hazards ahead.

Eye tracking has not been used to study the influence of driver stress on gaze behavior, but stress is an important component of cycling research. The stress results showed some reduction in gaze range in the x and y direction. In addition, as stress increased, the median gaze range decreased. Even more striking, the variance in gaze range decreased substantially moving from low to moderately high stress. In addition, stress seemed to decrease the number of fixations without a decrease in their duration. Although no results were statistically significant in this exploratory study of the influence of stress on gaze behavior, this research suggests that stress does influence gaze and warrants further, more specific study with a wider distribution of stress levels during rides.

5.6 Conclusion

Gaze behavior is linked to cyclists' safety and can help inform design decisions both now and as we prepare for autonomous vehicles, but it is one aspect of cyclist safety research that is in its early stages. This paper presented new methods and directions for further study of cyclists' gaze behavior. This initial exploratory study has shown that gaze behavior can be used to understand the scanning strategies of cyclists and the stress of cyclists. Overall, the results suggest that stress may influence gaze, but whether cyclists self-rate as having stronger safety motives or not has a stronger influence on gaze behavior. This finding pairs with the suggestion from the statistical analysis that there were large individual differences, collectively suggesting that strategies vary based on cyclists' safety motives. It seems that task or other factors are more important to gaze measures studied here than complexity. Future study should focus on cyclists' skill, experience, and stress. Studies of complexity may be better suited to consistent tasks with outside factors such as conversation increasing that complexity. Furthermore, this study has shown how stress, skill, and complexity influence gaze without the influence of heavy motor vehicle traffic and can thus serve as a foundation upon which we can layer studies of gaze behavior in mixed traffic situations.

This study also used some unconventional methods of data analysis/measures. The use of distribution measures rather than areas of interest was useful in identifying differences in visual search strategy by cyclists' stated skill. It provided a description of where cyclists looked generally and their gaze area. Furthermore, the combination of boxplots with measures of gaze area was useful to identifying that one group of cyclists (high motor-tactical skills) tended to have a smaller gaze area, but that gaze area varied widely in location in the frame of view. Either measure alone would not have been able to show this. This has demonstrated that these measures can further our understanding of gaze behavior.

Although this study was exploratory and theoretical in nature, it has some practical implications. First, safety motivations are important to improved safety-relevant gaze, even for skilled cyclists. Therefore, safety motivated behaviors, such as scanning intersections or checking parked cars' doors, could be encouraged. Additionally, this study further confirmed that bumpy pavements can lead to lower gaze than smooth pavements. Lower gaze could result in missed safety-relevant cues, so improving ride quality may serve safety purposes as well.

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CHAPTER 6. INFLUENCE OF PAVEMENT FEATURES ON CYCLISTS' PERCEPTION OF SAFETY AND COMFORT: A COMBINED SURVEY AND EYE TRACKING STUDY

Abstract

Although infrequently included in studies of cyclists' perceived safety, pavement condition impacts cyclists' stress and related perceptions of safety. Few studies investigating pavement's impact on cyclists' perceived safety have gone far enough to develop actionable information for industry professionals. This paper aims to fill that gap by identifying which pavement distresses most influence cyclists' perceived safety and comfort and making recommendations of how maintenance should be prioritized based on the results. This study used a combination of online surveys and field experiments. The 181 complete responses to the online survey showed potholes were the most important pavement distress for perceived safety and comfort and debris, wide cracks, and unevenness were also important. Eye tracking data was collected during the field experiment and analyzed for whether participants fixated on the distresses, when, and for how long. These results showed that unevenness attracted the most fixations for the longest duration. In mixed traffic scenarios, participants tended to fixate less frequently and closer to the object compared to the separated facility suggesting a potential safety concern. These findings are compiled into recommendations for cyclist-focused maintenance practices. These recommendations can be used by asset management planners and maintenance personnel to improve the perceived safety and comfort of their cycle network.

6.1 Introduction

Cycling is a low-cost, low-emission means of transportation that can fill gaps in our transportation system and improve public health. Despite the evidence that the health benefits outweigh the risks (*1*), cycling is often viewed as unsafe and stressful (*2*, *3*). Perceived safety and stress are key concerns in the design of cycling facilities. It is well established that motor vehicles, high traffic speeds, and mixed facilities increase cyclists' stress (*4*–*9*).

Rating systems have been designed to address the perceived safety and stress of cycling. One of the most well-known of these ratings systems, Level of Traffic Stress (LTS) rates facilities from 1 (low stress) to 4 (high stress) based on the infrastructure and cyclists' comfort (*10*). LTS attempts to create a rating system that is user-oriented and applicable across a network and considers bicycle facility presence and width, parking presence, speed limit, bicycle lane blockage, and the number of lanes (*10*). A predecessor to LTS and frequently used rating system, Bicycle Level of Service (BLOS) includes traffic volumes, number of through lanes, lane width, speed limit, volume of heavy vehicles, and pavement condition. BLOS was developed in one of the few studies of cyclists' comfort or stress that considers pavement as a stress inducer. Recent findings from a study that used self-reported causes of cyclists' stress and real-time interviews have found that pavement condition was the second most mentioned stressor when combining responses from Atlanta, in the United States and Delft, in the Netherlands (*9*).

As agencies build more cycling infrastructure, they need to incorporate pavement condition for cyclists into asset management practices. A review of Complete Streets asset management policies in the United States revealed a lack of condition assessment for cycling facilities (*11*). To incorporate cycling infrastructure into asset management, agencies need to identify what pavement condition features matter, as well as how to rate the condition for prioritization and how to collect that data. Most studies concerning cyclists' comfort have not linked to asset management and have not defined what aspects of the pavement were important.

Two studies have tried to incorporate cycling infrastructure into asset management. Thigpen et al.'s study used accelerometers to measure cyclists' comfort and linked that to mean profile depth (MPD), a common pavement measurement (*12*). However, the study did not specify specific pavement conditions of concern and focused on recreational cyclists and major roads owned by Caltrans, primarily rural roads. In England, Calvey et al. designed a bike with accelerometers to collect pavement condition data relevant to cyclists (*13*, *14*). They used this bike in conjunction with survey data to better understand the factors that influence cyclists' safety and comfort. They included debris and surface defects in their survey, which came out as the two highest concerns, ranked worse than the directness and width of the path. Although Calvey included some types of pavement concerns, it was not sufficiently complete as surface defects could have a wide range of solutions. Although these studies have increased our understanding of cyclist comfort related to pavement, they have not yet gotten to the fundamental question of what features of pavement condition should be prioritized for maintenance to support safe, comfortable cycling.

The study that is the subject of this paper aims to fill that gap using a combination of survey data and eye tracking to gain an understanding of what cyclists perceive as unsafe and uncomfortable and how that relates to gaze behavior and attention under different levels of separation from motor vehicles. The results will identify what pavement condition features should be prioritized in 3 scenarios: fully separated, bike lane, and mixed traffic. These findings will be valuable for agencies building bicycle facility asset management systems.

6.2 Methods

The purpose of the data collection was two-fold. The first goal was to understand what pavement conditions impact cyclists' sense of safety and comfort on varying road configurations. The second was to understand how pavement conditions influence gaze behavior and if gaze behavior aligned with the participant's survey results. To do this, both survey techniques and naturalistic cycling methods were used.

The study took place in Atlanta, Georgia, USA, which has a population of approximately 500,000 with approximately 6 million people in the metro area. Atlanta had a 1.4% bicycle modal share in 2016 (*15*) and 17% modal share for bike/walk/transit in 2018 (*16*). The online survey was administered from June-September 2020 and eye tracking data collection took place October–December 2020.

6.2.1 Participants/Recruitment

The survey was sent out through various biking groups in Atlanta, including bike commute list serves for universities and companies, cycling-related social media pages, group ride hosts, cycling advocacy groups, and bike shops. An effort was made to gain a diverse sample representative of Atlanta and care was taken to reach out to predominately minority cycling-related organizations; however, the sample over represents white, highly educated people. In total, the survey had 181 complete responses. Of the respondents, 143 identified as white and 109 had a graduate degree. The sample contained 83 women (46%). Further discussion of the demographics and survey responses can be found in the Results section.

Due to concerns regarding the Covid-19 pandemic, the field experiments recruited only people affiliated with Georgia Tech. In total there were 17 participants, 8 women. Most participants were in the 18-34 age range with only 5 participants over 35 years old. This was expected because of the university-focused recruitment efforts.

6.2.2 Survey Instrument

The survey was administered online through the Qualtrics platform and designed to gauge how pavement condition influences cyclists' sense of safety and comfort on facility types differing in separation levels. The main portion of the survey contained short videos from a cyclists' perspective cycling on each of the facility types (separated cycle track, painted bike lane, mixed traffic). A screenshot of the video for each type of facility is shown in Figure 6-1. The video was intended to orient the respondent to that section of questioning. These video-based descriptive surveys have been shown to resemble responses in a real-world experiment with a slight negative bias (*17*). 7-point Likert style questions following each video asked how pavement features would influence their feelings of safety and comfort on that type of facility. These questions were asked for each facility type and demographic questions were asked at the end. The survey was slightly modified for the field experiment to add an identifier to link their eye tracking video to their survey response.

The seven features included potholes, debris, unevenness, narrow cracks, wide cracks, faded paint, and green paint. Debris was described as gravel, leaves, etc. and unevenness was described as bumpy road, spots of raised asphalt, low manhole covers, etc. Narrow cracks were described as closed and wide cracks as wide enough to feel. Colloquial terms and definitions were used for the pavement features because of the audience for the survey and the focus on their perspective. Therefore, there were no strict definitions (i.e. crack width in mm) or measures of pavement roughness (i.e. IRI). Examples of each feature can be seen in the map of Figure 6-3 displaying the features used for the eye tracking portion.

Separated | Bike Lane | Mixed Traffic

Figure 6-1 Screenshots of each facility type in the survey

6.2.3 Field Experiment Route

The route design targeted the most important pavement conditions from the survey. The route had segments of separated cycle track, bike lane, and mixed traffic. It was ridden clockwise by all participants. Figure 6-2 displays the route color-coded by facility type. Figure 6-3 displays the targeted pavement features.

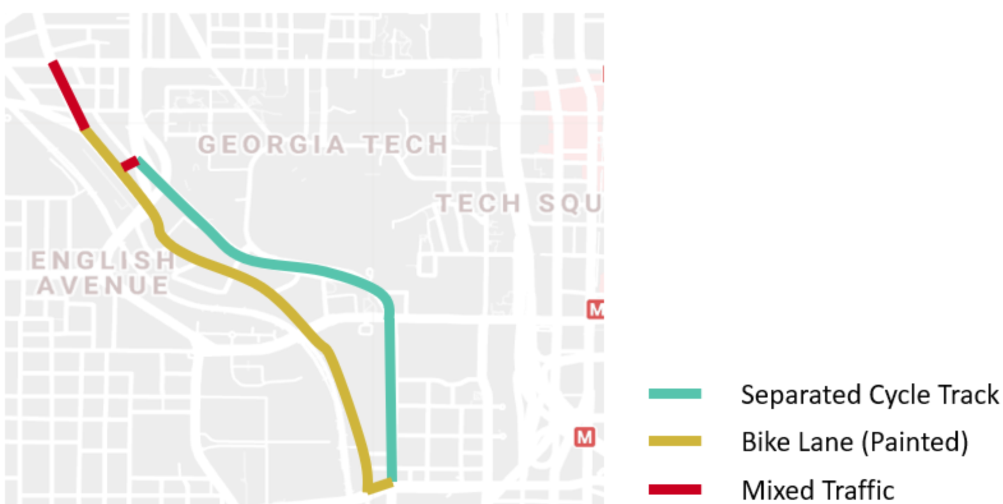

Figure 6-2 Data Collection Route color-coded by facility type.

Figure 6-3 Route map with selected pavement features

6.2.4 Sensors

Pupil Labs Invisible eye tracking glasses, pictured in Figure 6-4, were used for this study because they were designed to function well in sunlight and correct for slippage (*18*). The eye camera collects data at 200Hz.

Figure 6-4 Pupil Labs Invisible Eye Trackers used in this study.

6.2.5 Protocol

The protocol was approved by the internal review board at Georgia Tech and had special provisions in place to reduce the risk of transmission of Covid-19. These provisions included a pre-ride checklist for symptoms, masks, gloves, sanitation, and limited close interaction. A data collection appointment started with the participant meeting the researcher in a designated open, outdoor space. The participant signed consent forms, then the researcher reviewed the route with the participant. The participant then put on the eye trackers and the researcher confirmed that the eye trackers were collecting data and calibration was successful. After, the participant cycled the route clockwise on their own bike. At the end of the ride, the participant returned the eye tracking glasses and was emailed the online survey to fill out within 24 hours. To not bias their gaze, the participant was not aware that pavement was the focus of the study until they received the survey.

6.2.6 Analysis Methods

Both eye tracking analysis and survey analysis were needed. Each occurred separately, then the results were compared to see if gaze behavior matched their stated preferences.

6.2.6.1 Survey Analysis

The survey was analyzed using descriptive statistics, visual representation, and statistical testing. Initially, the intention was to use statistical modeling techniques such as regression, but after visual inspection of the data, it was clear there was no relationship to model. Instead, descriptive statistics and statistical testing were used in combination with visual representations such as bar graphs and density plots. Although Likert-type data is ordinal, literature supports that Analysis of Variance (ANOVA) is sufficiently robust to use, especially with large sample sizes (*19*, *20*). ANOVA is less conservative than a nonparametric test and more likely to find a relationship that does not actually exist. Because this study is about safety, there is more risk in missing a relationship than finding one that does not exist, so ANOVA's, and in cases of 2 groups T-tests, were used to assess statistical significance.

6.2.6.2 Eye Tracking

The eye tracking videos were reviewed to identify each of the pavement features. Fixations, which the Pupil Labs software could identify, were the focus of the analysis. The minimum fixation length was set to 150 ms and the maximum dispersion 4.5 degrees to capture the fixations despite movement associated with cycling. The videos were reviewed frame-by-frame to confirm the software-identified fixations.

The faded paint and green paint had no more than a slight impact on cyclists' perceived safety and comfort in the survey. The extent of paint features made it challenging to differentiate if the cyclist looked at it or just looked at their path of travel. Therefore, the paint features were not included in the eye tracking portion. The remaining features were visually identified in the video. The timestamp when the front wheel met the feature was recorded. Then the video was reviewed frame by frame back in time until the feature was not visible. The fixations on the object were recorded as well as the time stamp of the start of the first fixation. This information was then passed through a python code which compiled it into 3 measures. One a simple yes/no of whether they fixated on the object and the second was for how long. The third, referred to as "time to arrival" was the recorded time the front wheel met the feature minus the timestamp of the start of the first fixation. This was used because the longer the time to arrival of the first fixation, the longer the cyclist had to react to the feature making a longer time to arrival safer than a shorter. The complete analysis assesses whether the object was fixated upon, how long it was fixated upon, and how long before meeting the object was it first fixated upon (time to arrival).

6.3 Results

This section will review the results of the analysis starting with the survey portion of the study followed by the eye tracking portions.

6.3.1 Survey - Demographics

The sample demographics will be discussed first. The sample was 54% male and predominately white (79%). The sample was also highly educated, with 59% of the sample having a graduate degree and 35% a Bachelor's degree. As shown in Figure 6-5, the age groups were well distributed. The majority of respondents fell within the ages of 25-44 (58%).

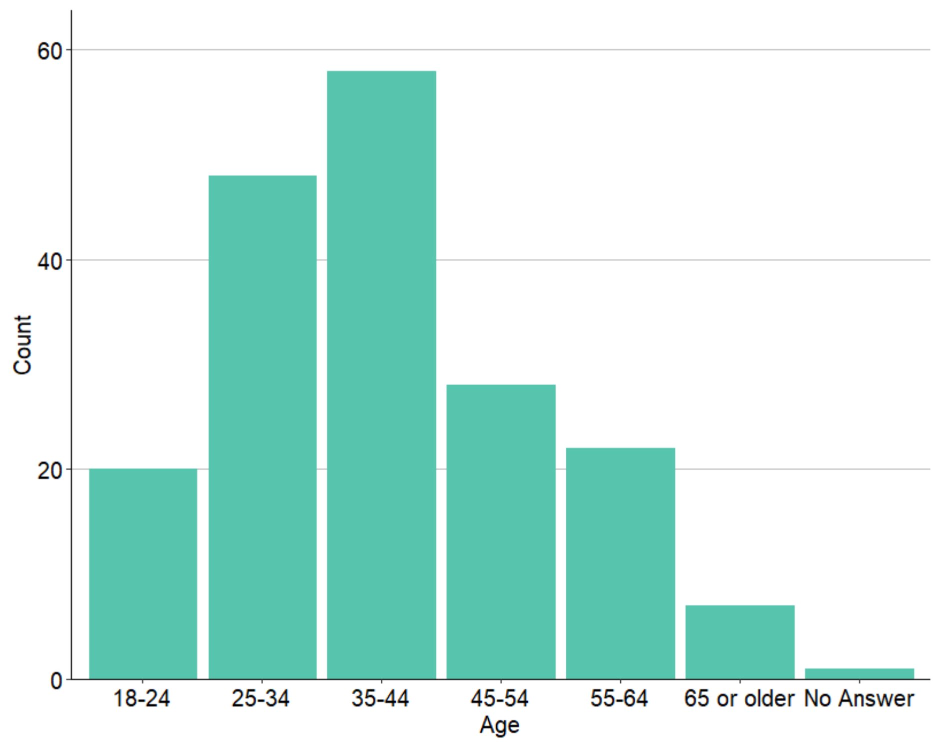

Figure 6-5 Histogram of ages in the sample.

The survey also asked about transportation habits and attitudes, including rider type, bicycle commute frequency, bicycle recreation frequency, and primary mode. The rider type was initially defined by Geller (*21*), but the modified one that includes "comfortable, but Cautious" from Misra (*22*) was used in this study . The most common response was "Enthused & Confident." The "Interested, but Concerned" group was under-sampled. This was expected because "Interested, but Concerned" cyclists are less likely to cycle in Atlanta and be in the email listservs or social media groups the survey was advertised in. The distribution of rider types can be seen in Figure 6-6. Car and bicycle were the most common primary mode, with 43% and 42% in each group, respectively. The sample had a good mix of commute frequency with the most common being daily (33%), shown in Figure 6-7. There was also a mix of recreational cycling frequency with the most in "several times/month" (43%), shown in Figure 6-8.

Overall, there was sufficient variation in age and transportation habits/attitudes to consider these variables in the statistical analysis.

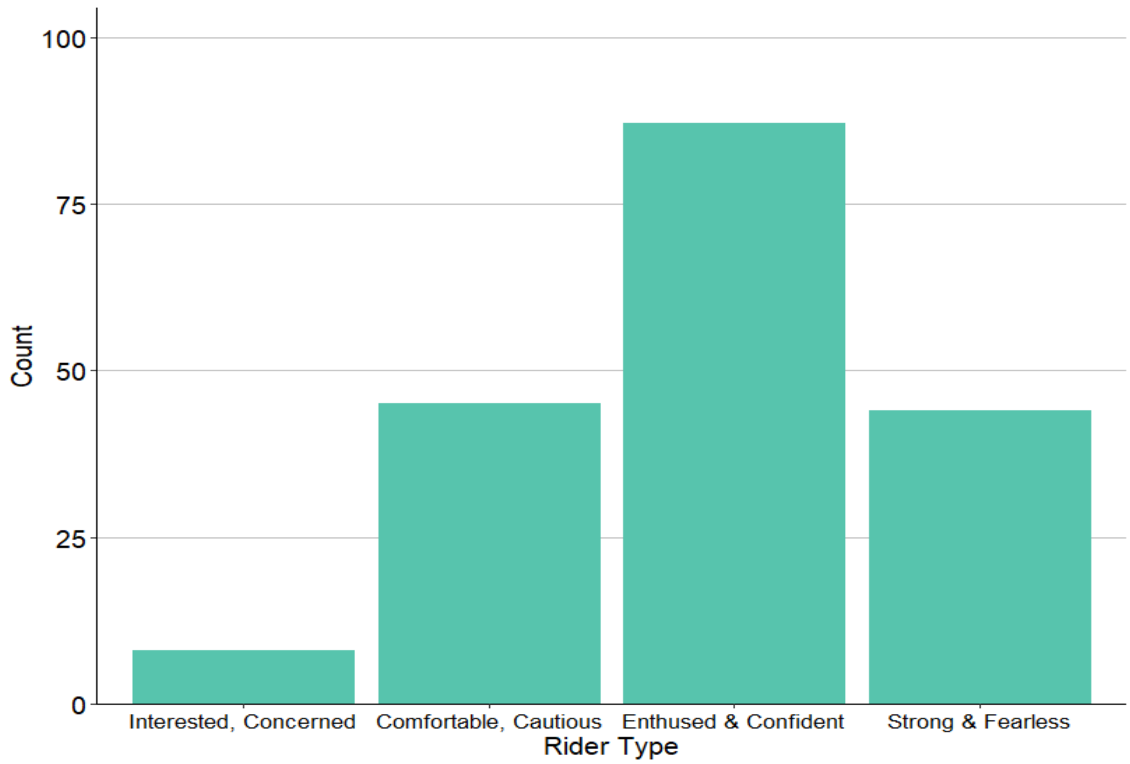

Figure 6-6 Histogram of rider types.

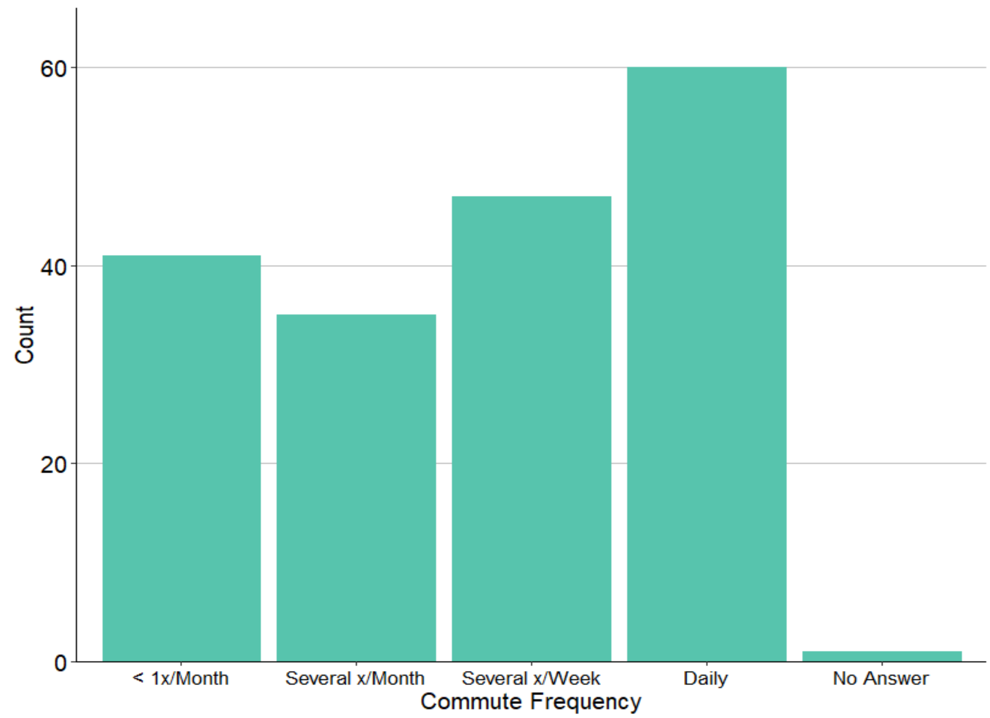

Figure 6-7 Histogram of commute frequency.

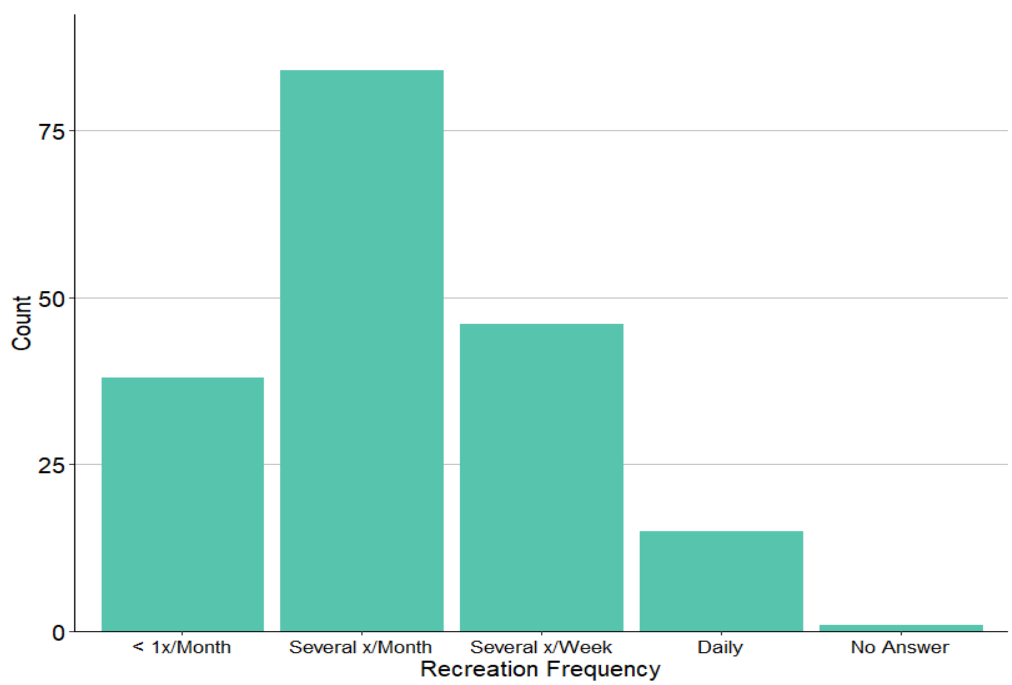

Figure 6-8 Histogram of recreation frequency.

6.3.2 Survey—Safety & Comfort

This section will present the results of the survey responses. Boxplots of the responses to how each pavement feature affected respondents' feelings of safety and comfort are provided in Figure 6-9 and Figure 6-10, respectively.

Based on the survey, the most prominent feature negatively impacting cyclists' feelings of safety are potholes followed by wide cracks, debris, and unevenness. The narrow cracks and paint only had minor to no impact. The pavement features tended to have less effect on feelings of safety in the separated facility scenario. The results for the bike lane and mixed traffic facility were nearly identical. The statistical analysis will focus on the conditions with at least a moderate impact: potholes, wide cracks, debris, and unevenness.

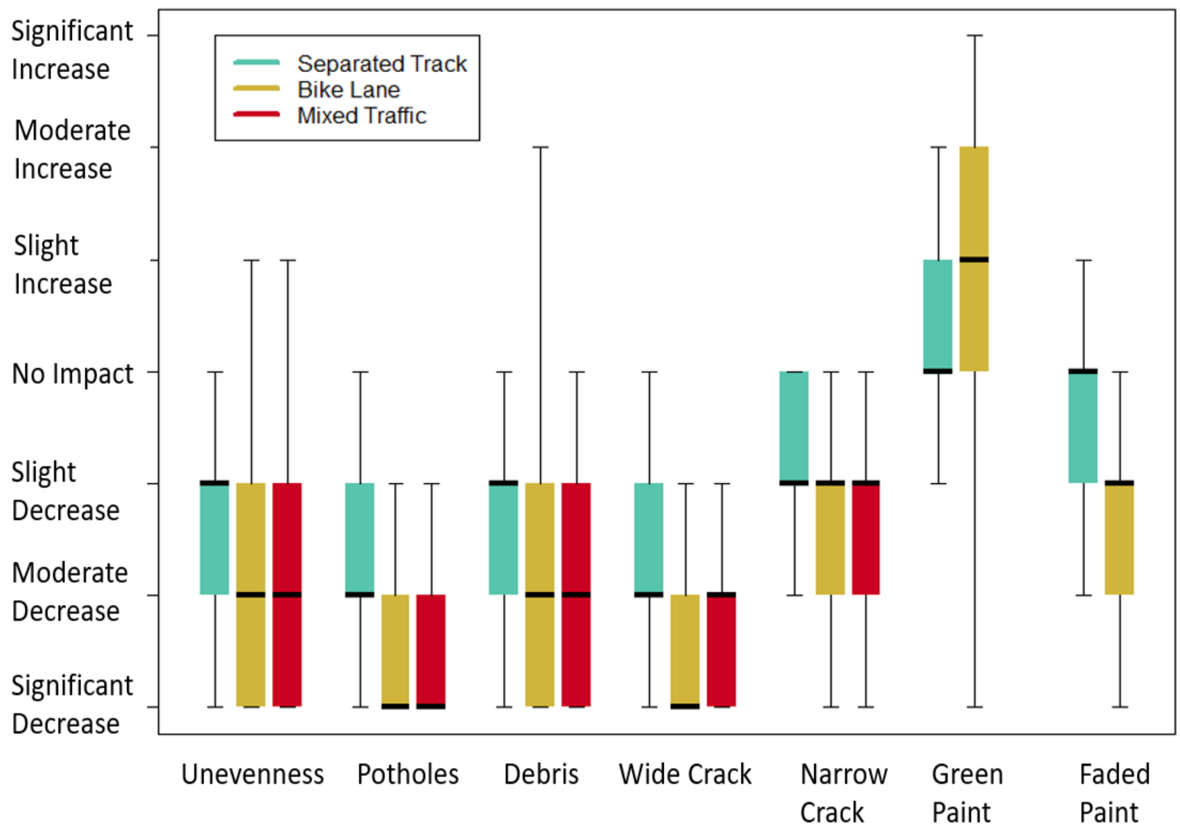

Figure 6-9 Boxplots by pavement feature for "In this scenario, how does encountering the following impact your feelings of safety?"

The results were largely similar for comfort. Potholes became less important on bike lanes, and unevenness became more important in the separated condition. Narrow cracks and green paint remained of low importance, so the same four conditions will be considered in the statistical testing.

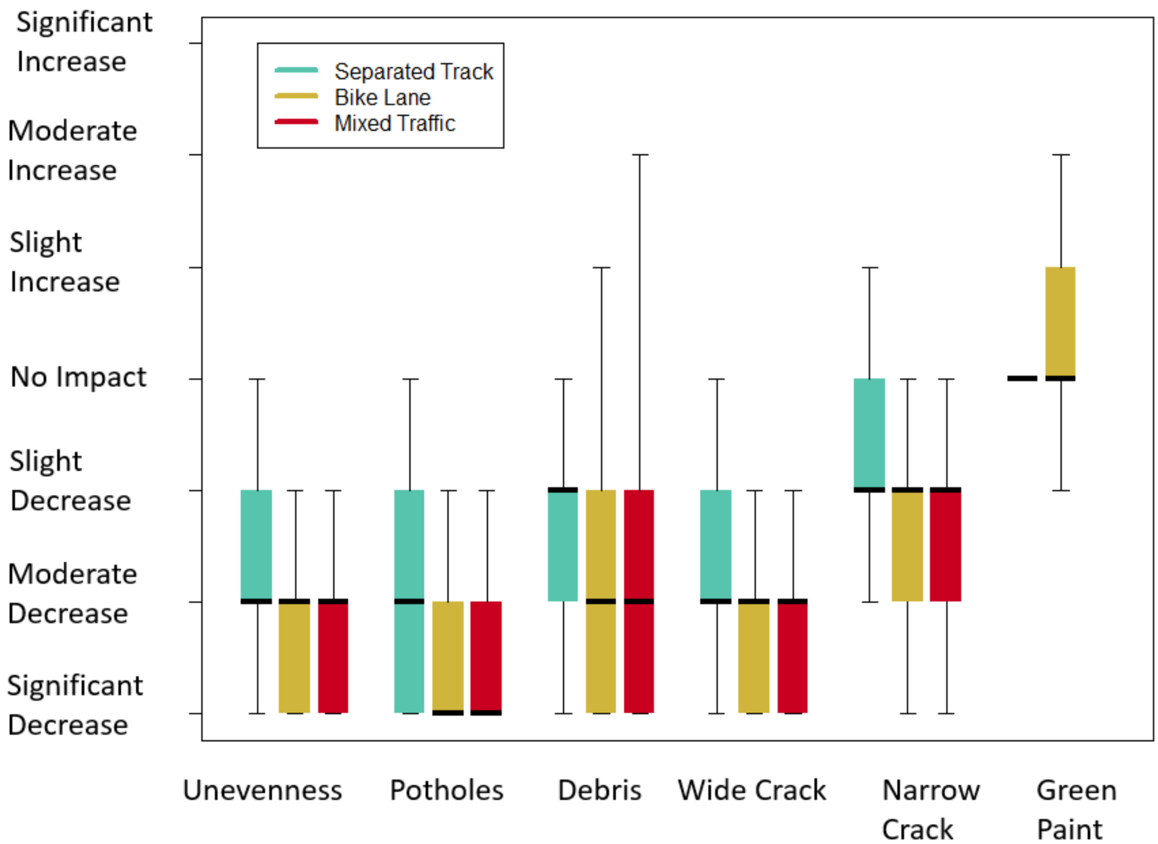

Figure 6-10 Boxplots by pavement feature for "In this scenario, how does encountering the following impact your comfort?"

After visual inspection of the data, there did appear to be some differences by age and primary mode, so ANOVA statistical testing was carried out. For primary mode, only car and bicycle were compared due to the low number of respondents who chose transit or walking. For characteristics that only had 2 groups to test, t-tests were performed. The resultant p-values are given in

Separated	Bike Lane

	ANOVA DF	Pothole	Uneven-ness	Debris	Wide Crack	Pothole	Uneven-ness	Debris	Wide Crack
Age	6	0.0936	**.00305 ****	**.035***	**.00768 ****	0.798	0.178	0.512	0.166
Gender	T-test	0.869	0.211	0.588	0.603	0.539	0.816	0.471	0.888
Primary Mode	T-test	0.265	0.69	0.901	0.277	**0.013***	0.601	0.499	0.549
Commute Frequency	4	0.288	0.443	0.571	**.0111***	0.0776	0.973	0.733	0.121
Recreation Frequency	4	0.812	0.135	0.938	0.126	0.35	0.0775	0.62	0.0652

		Mixed			
		Pothole	Uneven-ness	Debris	Wide Crack
Age	6	0.923	0.396	0.774	0.712
Gender	T-test	0.863	0.17	0.515	0.57
Primary Mode	T-test	**0.04***	0.097	0.261	0.65
Commute Frequency	4	0.401	0.712	0.493	0.481
Recreation Frequency	4	0.927	0.515	0.146	0.816

Table 6-1. The Tukey posthoc results can be found in the Appendix E. Posthoc Tests for Chapter 6.

Table 6-1 P values for the ANOVA and T-tests by demographics of interest and pavement feature for responses to impact on perceived safety. (* p<0.05; ** p< 0.01 ; *** p < 0.001)

		Separated				Bike Lane			
	ANOVA DF	Pothole	Uneven-ness	Debris	Wide Crack	Pothole	Uneven-ness	Debris	Wide Crack
Age	6	0.0936	**.00305 ****	**.035***	**.00768 ****	0.798	0.178	0.512	0.166
Gender	T-test	0.869	0.211	0.588	0.603	0.539	0.816	0.471	0.888
Primary Mode	T-test	0.265	0.69	0.901	0.277	**0.013***	0.601	0.499	0.549
Commute Frequency	4	0.288	0.443	0.571	**.0111***	0.0776	0.973	0.733	0.121
Recreation Frequency	4	0.812	0.135	0.938	0.126	0.35	0.0775	0.62	0.0652

		Mixed			
		Pothole	Uneven-ness	Debris	Wide Crack
Age	6	0.923	0.396	0.774	0.712
Gender	T-test	0.863	0.17	0.515	0.57
Primary Mode	T-test	**0.04***	0.097	0.261	0.65
Commute Frequency	4	0.401	0.712	0.493	0.481
Recreation Frequency	4	0.927	0.515	0.146	0.816

From

Table 6-1, age had a significant effect on how safe people felt related to unevenness, debris, and wide cracks on separated facilities. The Tukey results showed the difference in

		Separated				Bike Lane			
	ANOVA DF	Pothole	Uneven-ness	Debris	Wide Crack	Pothole	Uneven-ness	Debris	Wide Crack
Age	6	0.0936	**.00305 ****	**.035***	**.00768 ****	0.798	0.178	0.512	0.166
Gender	T-test	0.869	0.211	0.588	0.603	0.539	0.816	0.471	0.888
Primary Mode	T-test	0.265	0.69	0.901	0.277	**0.013***	0.601	0.499	0.549
Commute Frequency	4	0.288	0.443	0.571	**.0111***	0.0776	0.973	0.733	0.121
Recreation Frequency	4	0.812	0.135	0.938	0.126	0.35	0.0775	0.62	0.0652

		Mixed			
		Pothole	Uneven-ness	Debris	Wide Crack
Age	6	0.923	0.396	0.774	0.712
Gender	T-test	0.863	0.17	0.515	0.57
Primary Mode	T-test	**0.04***	0.097	0.261	0.65
Commute Frequency	4	0.401	0.712	0.493	0.481
Recreation Frequency	4	0.927	0.515	0.146	0.816

unevenness was between the “65 and older” group and the younger 18-24, 25-34, and 35-44 groups. The grouping of the younger half of the sample (18-44) and the older half (45+) can be seen in the density plot in Figure 6-11. The difference in response to wide cracks was between the 45-54 and 25-34 groups. None of the groups were significant for debris, so the slightly significant ANOVA may be a false positive. With so many statistical tests, this can be expected. It won't be considered further.

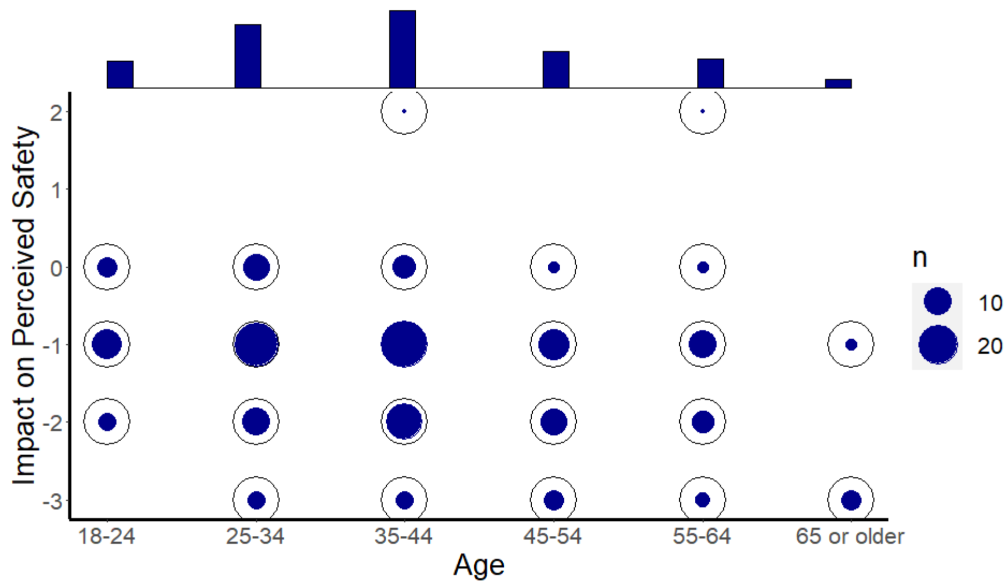

Figure 6-11 A density plot of the impact on perceived safety from unevenness on separated facilities with the size of the blue circle related to the count of responses at that point. The histogram on top shows the histogram for the age groups.

People whose primary mode was a car were more concerned about potholes than people whose primary mode was a bicycle, which was significant in the bike lane and mixed traffic conditions. Wide cracking on a separated facility showed a difference between the daily bicycle commuters and the "several times a month" bicycle commuting group. As can be seen from the density plot in Figure 6-12, the daily bicycle commuters had proportionally more responses in "substantial decrease" and less in the "no impact" category.

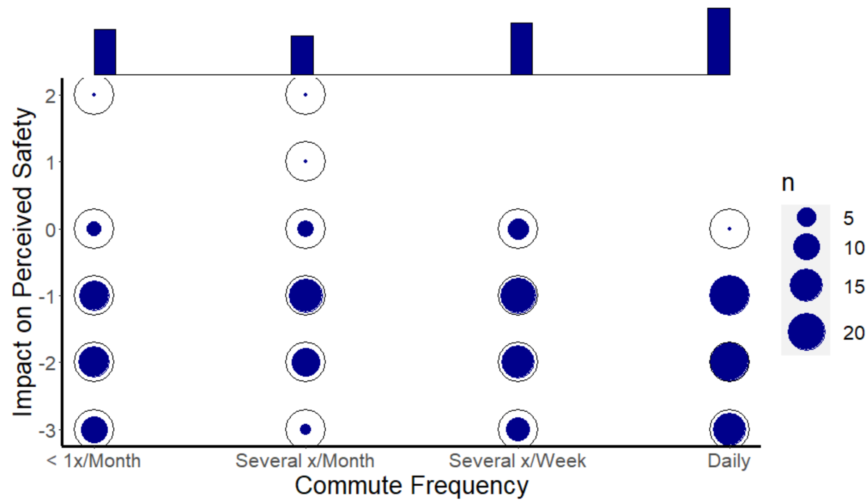

Figure 6-12 A density plot of the impact on perceived safety from wide cracks on a separated facility with the size of the blue circle related to the count of responses at that point. The histogram on top shows the histogram for the bicycle commute frequency.

The same statistical testing was performed for the comfort scores. The results are shown in Figure 6-13.

Table 6-2. The only significant results were for the recreation frequency groups for wide cracks on separated and mixed facilities. The Tukey Posthoc results did not show any significant differences at a 95% confidence level for wide cracks on separated facility by bicycle recreation frequency. This was again only slightly significant in the ANOVA and could be a false positive. For the mixed facility, the differences were attributed to the "several times per month" and "daily" groups. The density plots suggest the differences may be more associated with the difference in the size of the two groupings, resulting in proportionately more responding moderate or substantial decrease in safety for the "several times per month" groups than the "daily" groups. The density plot is provided in Figure 6-13.

Table 6-2 P values for the ANOVA and T-tests by demographics of interest and distress type for responses to impact on comfort. (* p<0.05; ** p< 0.01 ; *** p < 0.001)

		Separated				Bike Lane			
	ANOVA DF	Pothole	Uneven-ness	Debris	Wide Crack	Pothole	Uneven-ness	Debris	Wide Crack
Age	6	0.301	0.0802	0.0836	0.112	0.978	0.178	0.512	0.166
Gender	T-test	0.489	0.756	0.913	0.885	0.463	0.474	0.679	0.396
Primary Mode	T-test	0.616	0.213	0.778	0.823	0.115	0.408	0.323	0.582
Commute Frequency	4	0.792	0.443	0.772	0.743	0.455	0.629	0.376	0.915
Recreation Frequency	4	0.349	0.169	0.889	**0.0346** *	0.798	0.14	0.707	0.194

		Mixed			
	ANOVA DF	Pothole	Uneven-ness	Debris	Wide Crack
Age	6	0.867	0.855	0.791	0.961
Gender	T-test	0.664	0.378	0.56	0.705
Primary Mode	T-test	0.091	0.766	0.112	0.442
Commute Frequency	4	0.36	0.76	0.286	0.693
Recreation Frequency	4	0.574	0.224	0.417	**0.0161** *

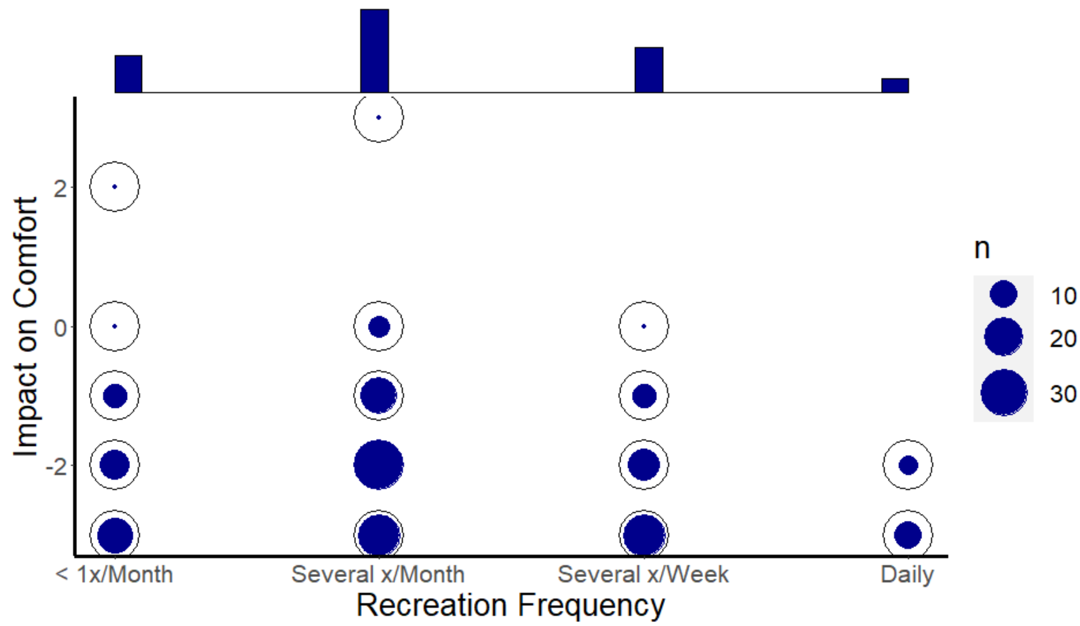

Figure 6-13 A density plot of the impact on comfort from wide cracks on a mixed facility with the size of the blue circle related to the count of responses at that point. The histogram on top shows the histogram for the recreation frequency.

6.3.3 Eye Tracking

As can be seen in Table 6-3, the eye tracking results showed that overall, unevenness tends to be the most fixated upon, for the longest, and with the largest time to arrival. The pothole on the separated facility was the exception. It was fixated upon more frequently and for longer than the unevenness in the separated cycle track. Debris and potholes were fixated upon less frequently, for a shorter time, and closer to arrival on the mixed traffic facility than on the separated cycle track or bike lane. In contrast, unevenness was fixated on for slightly longer and more frequently, but with less time to arrival on the mixed facility.

The cracking was overall less important in terms of gaze behavior. Cracking to the point of unevenness may be a concern, but these findings suggest that debris, potholes, and general unevenness are more important for cyclists' gaze behavior.

Table 6-3 The Eye tracking measures by distress type and lane type.

Infrastructure	Percent Fixating	Median Fixation Length (ms)	Time to Arrival from 1st Fixation (s)
Pothole			
Separated	82%	610	1.9
Bike Lane	82%	416	1.1
Mixed	47%	188	1.0
Unevenness			
Separated	71%	534	3.4
Bike Lane	88%	548	2.5
Mixed	93%	560	2.3
Debris			
Separated	65%	332	2.4
Bike Lane	65%	384	1.9
Mixed	40%	188	1.3
Wide Crack			
Separated	59%	268	1.2
Bike Lane	29%	232	1.1
Mixed	47%	272	0.9
Minor Crack			
Separated	47%	246	1.4
Bike lane	N/A		
Mixed	20%	224	1.6

6.3.4 Eye Tracking—Surveys

The 17 eye-tracking study participants filled out the same online survey that was given to the larger online population after their ride. Boxplots of their responses are given in Figure 6-14 and Figure 6-15. Their responses overall tended to be less negative than the larger sample, but the order of importance remained similar. The less negative responses align with findings that survey-only respondents tended to respond more negatively than people who participated in a field experiment (*17*).

Potholes came out as having the most impact on perceived safety and comfort. Unevenness was a bit less important compared wide cracks and debris, at least in the bike lane and mixed scenarios, but drew the most gaze. This does not necessarily mean their survey responses contradict their eye tracking data, but that what attracts the most gaze and has the biggest impact on feelings of safety may not be the same. Both are important to cyclists' safety and perception of safety and must be considered.

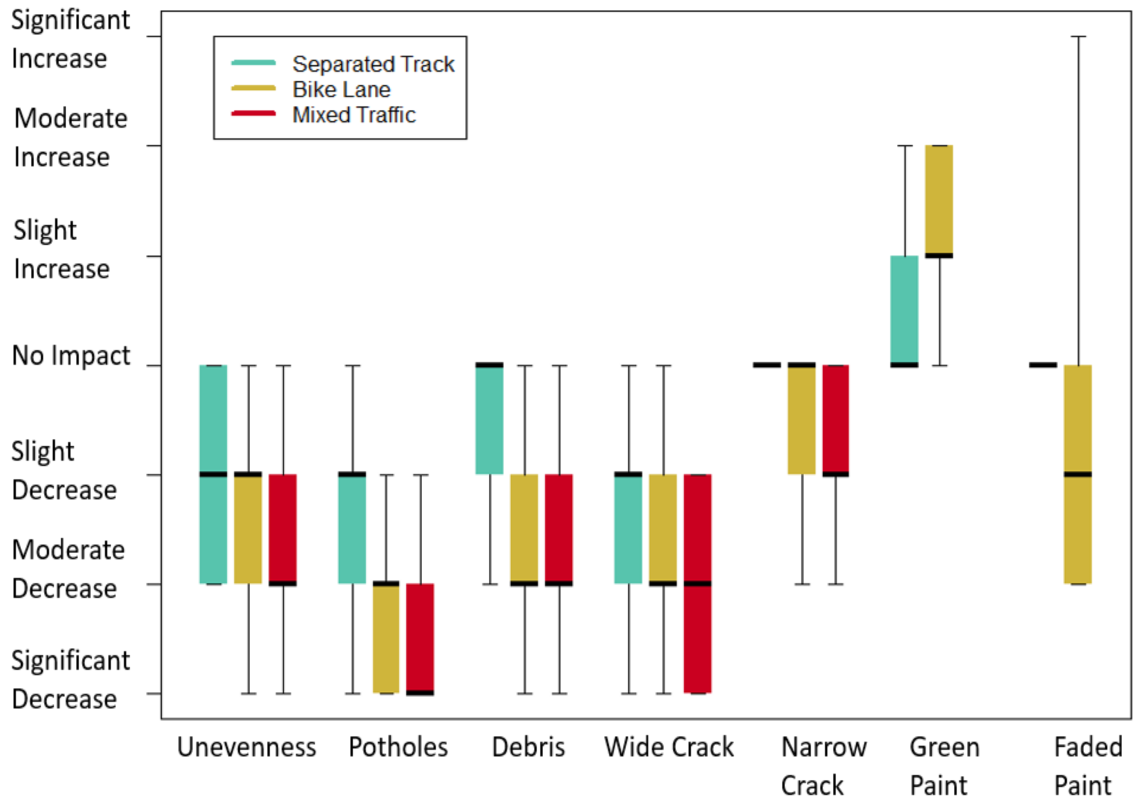

Figure 6-14 Boxplots for the field participant sample by pavement feature for "In this scenario, how does encountering the following impact your feelings of safety?"

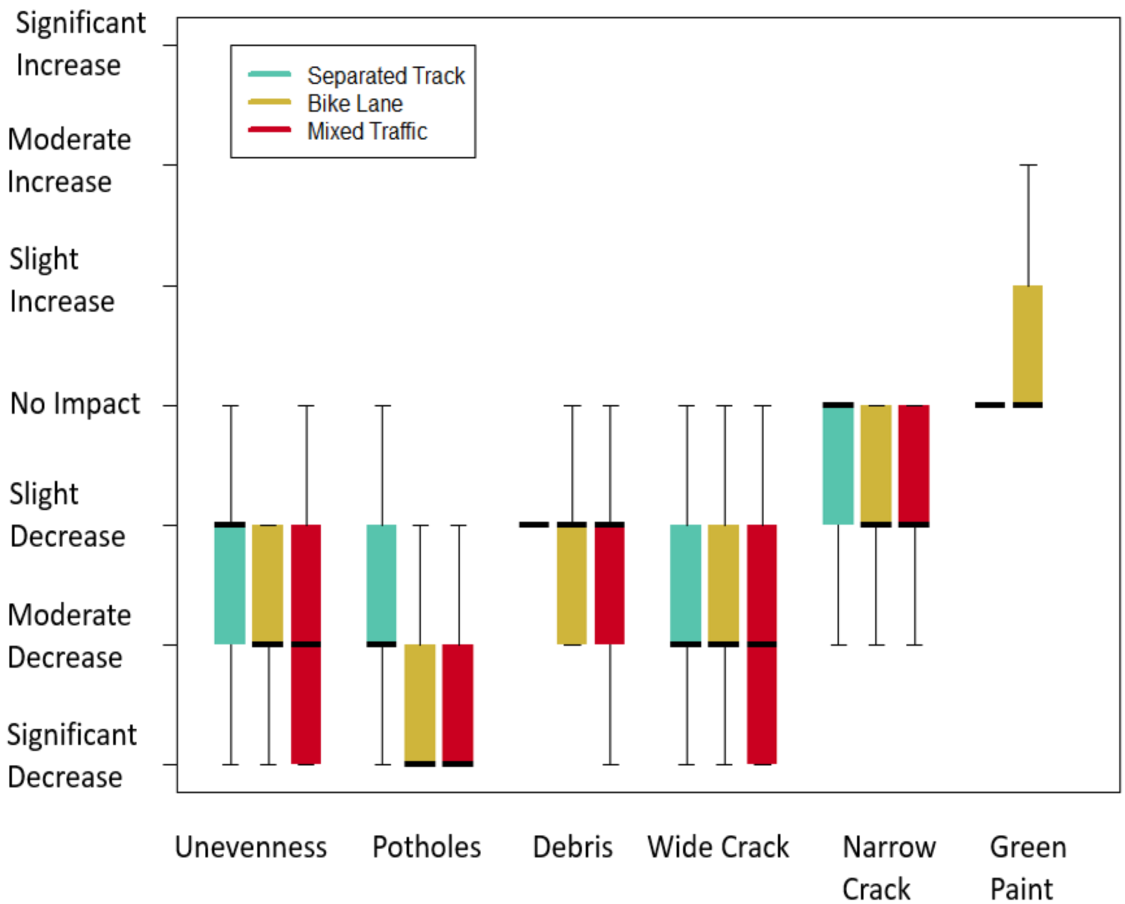

Figure 6-15 Boxplots for the field participant sample by pavement feature for "In this scenario, how does encountering the following impact your comfort?"

6.4 Discussion

The primary objective of this paper was to recommend which maintenance activities to prioritize to improve the bikability of the city. This prioritization was to be based on both survey responses on perceived safety and comfort and eye tracking data. The discussion will focus on what was learned and what the practical implications are.

The survey results demonstrated that potholes anywhere have a substantial influence on cyclists' perceived safety and comfort. This was true across all possible segmentation of the data (i.e. age, rider type, etc.). This suggests that filling potholes ought to be of the highest priority for infrastructure to feel safe and comfortable to those on bikes. Those driving as their primary mode were slightly more concerned about potholes than those cycling as their primary mode. This does not change the priority because everyone was highly concerned about potholes. However, it suggests that if the city hopes to increase cycling modal share, it is important to have pothole-free routes. Furthermore, it was notable that the participants of the in-field experiment had less negative responses to the pavement characteristics than the online-only participants, even though both took the survey online at their leisure. In Fitch & Handy's paper that found the same (*17*), they suggest this difference can be attributed to imagined vs experienced scenarios. This means people who are interested in cycling, but not yet cycling imagine it to be worse than it is, furthering the importance of having smooth pavements to encourage people to take up cycling as a mode of travel.

Interestingly, potholes did not draw the most gaze; instead, unevenness drew the most gaze. The survey put unevenness as slightly less important than debris or wide cracks, but unevenness was looked at more frequently, for longer, and earlier than these other distresses. This is important because it would be safer for the cyclist to be looking for other road users than at the pavement. It is important to note that gaze is associated with overt attention, but not covert. Covert attention is when someone attends to an object/target without fixating on it (*23*). Although fixations increase the likelihood a participant identified the object, it is possible that participants identified potholes without fixating on them. Therefore, the results of the eye tracking portion of this study and the survey do not contradict each other but provide two avenues for understanding how pavement influences cyclists' safety. A potential explanation for why unevenness drew more gaze than potholes despite having less effect on perceived safety could be associated with the extent, visibility, and avoid-ability of unevenness. Most of the uneven sections took the entire lane or close to it, so it was visible far in advance and demanded navigational planning. Potholes are typically much more compact and easier to avoid. In the eye tracking study, none of the potholes measured more than one foot in diameter. Therefore, cyclists may not need to linger their gaze on them to avoid the pothole.

Wide cracks and debris could have the same extent issue as unevenness. In this study, the wide cracks and debris were only a segment of no more than 10 feet. These components of extent and avoid-ability influencing gaze may be important to a successful maintenance plan. Wide cracks were important in the survey but drew much less gaze than debris, so cracking may not be as important to gaze behavior but is still influencing perceived safety.

The type of facility did have some effect on the results in both the gaze behavior and the survey analysis. For potholes and debris, cyclists observed them with less time to arrival on mixed facilities than on bike lanes or separated facilities. Literature has shown that increased visual tasks when driving result in shorter fixations (*24*). Cyclists would be experiencing many more safety-relevant cues when mixed with vehicles, so, it seems reasonable that/ they would see things later and give them less time. The reduced fixations on potholes and debris may mean that these safety-relevant cues are being missed in the mixed traffic situation. There is evidence that collisions go together with inadequate visual attention distributions, so this is considered a cause for concern and support for separation of modes. A simulator-based study may be needed to determine if cyclists in this setting are truly missing these pavement features and the influence on crash risk. Potholes and debris were fixated on less frequently and for a shorter duration on mixed facilities, but unevenness had a higher rate and length of fixation. The increased rate and length of fixation on unevenness further underpins the importance of having smooth (not uneven) pavement to allow cyclists' gaze to spend more time on other safety-relevant tasks such as observing surrounding vehicles or pedestrians.

For the survey responses, the results for the bike lane and mixed traffic were nearly identical, but the separated facility made all the pavement distresses less impactful on perceived safety and comfort. Distresses in a bike lane can send a cyclist into mixed traffic, so this result makes sense and suggests that maintenance efforts should be focused on bike lanes and mixed traffic. However, any conditions that a cyclist cannot easily avoid in a separated facility should also be attended to in a timely fashion.

It was hypothesized that some of the demographic or rider characteristics would influence the survey responses. There were a few significant effects including age on the perceived safety of unevenness on separated facilities, using a car as their primary mode on potholes' impact on perceived safety, commute frequency on wide cracks in a separated facility, and recreation frequency on comfort around wide cracks in mixed facilities. Although these influences may exist, none were consistent or extensive enough to suggest a reorganization of the priority based on the population. Ultimately, potholes, unevenness, wide cracks, and debris are important for the feelings of safety and comfort of all cyclists.

This work provided valuable insights, but there were a few limitations. As previously pointed out, attention can be overt or covert so whether or not a fixation occurred does not necessarily inform us whether the participant noticed the object. Further research, possibly in a simulator, could better inform whether pavement features not fixated upon are being missed and the safety implications. Furthermore, colloquial rather than strict definitions of the pavement features were used in this study, so it cannot inform specifically at what point a narrow crack becomes a wide crack or the diameter of a pothole needed to be a concern. Furthermore, the eye tracking study only considered one of each distress on each facility type. These limitations necessitate future research into the specific pavement feature requirements for asset management. Despite efforts to recruit a representative sample, the sample was predominately white and highly educated. Demographic and rider characteristics did not come out as important in this study, but future work may want to consider these further with a more diverse sample. Despite these limitations, plenty of valuable practical implications stem from this research.

6.4.1 Practical Implications

Potholes, debris, wide cracks, and unevenness were the most important pavement considerations. These have very different treatments and solutions. This discussion will take into consideration the ease of alleviating these concerns. Overall, all four could be better addressed through minor tweaks to maintenance protocols.

The discussion pointed out a few overarching pavement feature characteristics to consider in prioritizing them for maintenance. The first to consider is their perceived impact on safety which potholes had the most impact on. In addition, the features' extent, avoid-ability, and visibility should be taken into consideration. Visibility is increased with increased color contrast and extent, as can be seen in lowered manholes or poorly done patches. Of the three, avoid-ability should be the most important because unavoidable pavement features can push cyclists into dangerous cycling conditions and require more attention to navigate which draws attention away from other safety-relevant cues. Any asset management plan focused on cyclists should prioritize based on perceived safety, avoid-ability, extent, and visibility.

Of the four most critical pavement features to perceived safety, debris is the easiest to address. Debris is often scattered from the roadway into the bike lane during storms. Debris can damage tires, cause bikes to lose traction, and have a moderate impact on perceived safety and comfort. A solution to the debris problem is to run the street sweepers along bike lanes at a regular interval. Adding in street sweeping or shifting the route of street sweepers from the driving lane to the bike lane can be a quick, relatively low-cost improvement to cyclists' safety and comfort.

Potholes are the biggest concern for cyclists' perceived safety and comfort. Although potholes may be merely a comfort concern for drivers, potholes can result in crashes for cyclists. Because of reduced loads on the pavement from bicycles being lighter, bicycle facilities do not often develop potholes. Moving cyclists into dedicated bicycle facilities, even a bike lane, can reduce the effort needed to immediately repair potholes. Naturally, when potholes are reported, these should be patched in a timely fashion. However, on mixed facilities where cyclists are expected to travel, it is critical for safety that agencies prioritize these routes for pothole filling activities. New pothole filling mix designs and protocols may be needed because it is likely for cyclists' safety that potholes of a smaller size would need to trigger maintenance activities than what triggers pothole filling for motor vehicles. Furthermore, it is important to not create an uneven surface when filling potholes. A shift in priorities to frequent bike routes could be an immediately applicable change and the new mix design could be a long term solution.

Unevenness is a broad category with many causes. Some are costly to rectify, such as raising grates. But a substantial amount of unevenness on roadways is caused by pothole filling or utility maintenance. These could be addressed by having stricter regulations on utility companies when they fill in pavement after a repair and by holding maintenance personnel to a higher standard. If money is available, rectifying unevenness issues such as low grates would be most valuable on bike lanes where this level of unevenness could make that portion of the bike lane unusable, sending cyclists into mixed traffic. If cyclists must enter mixed traffic, then the level of traffic stress for the route is increased and may reduce people's willingness to cycle.

Wide cracks are a challenge. Due to reduced loads on the pavement from bicycles being lighter, wide cracks are less likely to develop on bike facilities. The bike lanes will probably be repaved with the driving lanes which are likely to need repair sooner than the bike lanes. A minimum repaving date could be set based upon the time it is expected to take for the bike lane to weather to the point of having substantial cracking. Similarly, separated facilities should be repaved before substantial cracking makes the facility unusable. This timing could be developed through experience over time. Mixed facilities where cyclists are expected to travel should be prioritized for crack abatement.

6.5 Conclusion

This research further explored cyclists' perception of and gaze behavior around certain pavement features to improve maintenance practices to support cycling. Few papers have considered the impact of pavement condition on cyclists' feelings of safety and even fewer have extended that to existing maintenance practices. This research has answered what pavement features matter most and in what context. The results showed that potholes, unevenness, debris, and wide cracks have moderate to substantial impacts on cyclists' feelings of safety and comfort. In addition, eye tracking analysis showed that unevenness attracted the most gaze. All of these conditions were slightly less concerning on a separated cycle track compared to bike lanes or mixed facilities. Similarly, cyclists spent more time observing individual pavement distresses and were more likely to fixate on them with more separation. These findings have implications for both cyclists' feelings of safety and their actual safety. Maintenance practice recommendations were provided and supported basing maintenance prioritization on perceived safety, avoid-ability, extent, and visibility. Future studies could extend this work to determine if the reduced likelihood to fixate on distresses in the mixed traffic setting does indicate that the higher visual load is leading to missed hazard identification.

6.6 References

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CHAPTER 7. CONCLUSION

This chapter summarizes the main findings and the resulting contributions and limitations, then suggests directions for future work.

7.1 Contributions

This dissertation's contributions are first summarized by answering the research questions put forth in the introduction.

1. *When allowed to self-define stressors, what do cyclists identify as stressful? Does this vary between an emerging and an established cycling city?*

   CHAPTER 4 addressed this question through a combination of in-ride surveys and instrumented bicycles in quasi-naturalistic cycling. The study was performed in both Atlanta, an emerging cycling city, and in Delft, the Netherlands, a long-established cycling city. Although there were differences in stressors between the cities, the top stressor in both locations was motor vehicles. This demonstrated the importance of separation between modes to cyclists' stress.

   Another important finding was that cyclists in Delft spoke of their own speed and getting to choose their speed, whereas Atlanta cyclists spoke of the motor vehicles speeds. Further study with the instrumented bicycle data revealed that cyclists in Atlanta were going over twice as fast as Delft cyclists. Combined, these results suggest that cyclists in Atlanta feel pressured to cycle faster than they would without pressure from motor vehicles. Furthermore, pavement condition, an infrequent consideration in cyclists' stress studies, was revealed to be one of the top 3 stressors in both locations. Overall, the results suggest that cyclists, regardless of where they live, are less stressed when separated from motor vehicles by well-maintained bicycle infrastructure.

2. *How does gaze behavior vary with stress, complexity, and stated skill?*

   This exploratory question is investigated in CHAPTER 5 using a combination of eye tracking and survey techniques. The most striking results were the differences among cyclists self-identifying their skills as being high in motor-tactical type skills/low in safety motives and those who responded the opposite. Skill influenced the range of their gaze, but in unexpected ways. Although literature on drivers suggested that skilled drivers had a wider gaze range, this study found the opposite was true among cyclists. This could be because high safety motives are more associated with scanning behavior than high motor tactical skills. Furthermore, this suggested that researchers cannot assume the gaze behavior of drivers and cyclists are the same.

3. *Which pavement conditions matter most to cyclists' perceived safety and comfort?*

   This was answered in CHAPTER 6 using a combination of online surveys and eye tracking experiments. The surveys showed that, when asked about feelings of safety and comfort, cyclists care most about potholes followed by wide cracks, debris, and unevenness. Unevenness drew the most gaze. Participant characteristics did not have a strong influence on these hierarchies. Combined, these results suggest that for bike-able cities, maintenance needs to prioritize potholes, unevenness, wide cracks, and debris.

4. *How does the gaze given to pavement conditions vary by condition type and infrastructure type?*

   This question was also explored in CHAPTER 6. The field experiment cyclists had similar survey responses to the survey-only population. However, cyclists spent the most time fixating upon and were most likely to fixate upon unevenness. Their gaze could be better used to watch for hazards and other road users, so this highlights the importance of creating smooth riding surfaces.

   In mixed traffic scenarios, cyclists were less likely to fixate upon and spent less time fixating upon pavement distresses. This suggests cyclists may miss pavement hazards when cycling mixed with motor vehicles. This both supports separating cyclists and motor vehicles and prioritizing maintenance on mixed traffic facilities where cyclists are expected.

   Findings in CHAPTER 6 filled a gap in the existing literature. Existing literature has explored cyclists' reaction to pavement roughness that can be measured by accelerometers but has failed to capture distresses that a cyclist may not bike over. The literature had yet to define what pavement features were most important for cyclists' sense of safety and comfort which is critical information for asset managers. This chapter filled that gap. It demonstrated the importance of potholes, unevenness, debris, and wide cracks and that the extent, visibility, and avoid-ability of pavement features should be included in any cyclist-focused asset management plan.

5. *Can the use of in-ride survey techniques in combination with instrumented bicycles improve understanding of cyclists' stress?*

   The combined results from the three studies presented in this dissertation have allowed new insights into what cyclists consider most stressful, how gaze varies with stress and skill, and how to prioritize pavement maintenance for safe, comfortable cycling. The method of combining in-ride survey techniques with instrumented bicycles was highly successful in exploring the questions presented and could be used to explore many more research questions. Some of these will be covered in section 7.3 Future Research.

Combined, these studies have demonstrated the value of naturalistic cycling, smooth and separated cycle tracks, and designing from a cyclists' perspective. The common thread throughout these studies was the use of naturalistic cycling in combination with sensing and surveys. These methods allowed for new insights into cyclist behavior and design.

The approach used in this dissertation combined surveys and sensing techniques in naturalistic cycling. Previous research focused on cyclists' stress focused on surveys without the naturalistic cycling component or included the naturalistic cycling without a robust survey. Using in-ride surveys allowed for cyclists to describe their stress in near real-time. Literature shows that survey responses are less negative after a cycling experience (*1*), so it stands to reason that cyclists would also respond differently to more open-ended questions in the midst of a ride.

There are two other options to collect this data that are not truly naturalistic. These would be 1) on a test track and 2) in a simulator. The three (including naturalistic cycling) have varying degrees of trade-off between closeness to reality and control over the experimental conditions. Naturalistic cycling allows for the most realistic conditions but has the least control. Although the route could be predictable for the most part, the presence and actions of surrounding road users is largely unpredictable. This unpredictability requires more trials to ensure a sufficiently large, usable dataset. A test track presents much more control than naturalistic cycling but removes much concern for safety which is an important component of cyclists' stress. Test tracks are also very costly to construct and require large amounts of space that are not typically available, especially for research on cycling. Research comparing responses in naturalistic settings and a constructed to feel realistic test track may show that a test track allows for very similar responses, but with greater control. Unfortunately, although it has the possibility of being the most effective option, the costs of constructing one are prohibitive.

The last approach would be to use a simulator. This option presents the most control, but is the least realistic. Cycling simulators suffer from missing important cues such as the feeling of the air passing the cyclist, the pressure difference of a close pass, and the feeling of turning the bicycle. A participant clearly has no concern about their safety in such an environment which may impact their stress. A benefit to cycling simulators is that a broader cross-section of the population may be willing to participate in the study. Participants who are concerned about their safety when cycling will not participate in a naturalistic study but may in a simulator study. A simulator may be the best option, if available, for studies of hazard identification or differences between "interested, but concerned" and "strong and fearless" cyclists for safety concerns and to attract participants, respectively.

The approach used in this study presents the most realistic scenarios, and thus is the best choice among these for studying cyclists' stress. The approach used here was also low-cost and allowed for use of the existing infrastructure, making it accessible to any researcher within proximity of a bike-able road. It was innovative in its combination of techniques and allowed for new insights into cyclists' stress and behavior. For some studies, a simulator may be the ideal choice, so careful consideration should be given when selecting which method to use. However, one contribution of this work was to demonstrate that in-ride surveys with naturalistic cycling and instrumented bicycles is a feasible method for studying cyclists' behavior.

Eye tracking is another research method that has infrequently been used in cycling research. The research within this dissertation demonstrated some of the benefits of the approach as well as caveats. Eye movement is influenced by many external variables such as person-to-person differences that are not immediately relevant to the study. However, it can be challenging to recruit high enough numbers of participants for a naturalistic cycling experiment to adjust for these factors. When data collection completed for the study in CHAPTER 5, it has a larger sample size than any published eye tracking in naturalistic cycling study. Because of these external sources of variability, the statistical testing resulted in few significant results when trying to describe gaze behavior in a general manner as was attempted in CHAPTER 5. Despite these challenges, some valuable insights were gleaned, particularly about the differences between cyclists' motor-tactical skills, safety motives on gaze behavior and how those differed from expectations based on literature on drivers' gaze behavior. The technique was effective as an exploratory study, but more concrete results were possible when choosing a narrower scope as was done in CHAPTER 6. The narrow, focused scope allowed for less influence from outside factors, more significant results, and more practical findings. The research demonstrated that eye tracking can be used for both exploratory studies and practical, focused studies to gather valuable findings. But, it also demonstrated that the more focused scope allows for greater control and more significant results.

In addition to findings about the methods, there were important findings about cyclists' behavior and stress. A theme that arose during the research was the value of a smooth riding surface. Although previously pavement condition had rarely been considered in studies on cyclists' stress, CHAPTER 4 demonstrated that poor pavement is one of the top three most cited stressors among cyclists. CHAPTER 5 demonstrated that poor pavement can be a safety concern as it leads to lower gaze, potentially resulting in missed safety cues that would've been seen if the cyclist had been looking further ahead. CHAPTER 6 expanded on these findings to show that the most important components of poor pavement are unevenness, potholes, debris, and wide cracking. This study also demonstrated that decreased separation between cyclists and motorists resulted in a decreased likelihood that a participant fixated on one of these pavement concerns. This emphasizes the safety concern further. This information leads to implementable maintenance strategies, such as street sweeping bike lanes and setting stricter requirements on utility maintenance patching, to improve the comfort and safety of roadway facilities for cyclists.

Furthermore, the research showed that cyclists' behavior and needs may not follow the trends expected from literature on drivers. CHAPTER 6 suggested that pavement maintenance strategies need to consider that inconveniences for a driver (i.e. a mid-sized pothole) may be a safety concern for a cyclist. CHAPTER 5 also demonstrated that the gaze behavior of cyclists did not align with expectations based on the driving literature. Again, demonstrating that when designing for cyclists, engineers and planners cannot assume that cyclists will behave a certain way based on knowledge of drivers. Cyclists need to be considered through all aspects from planning to design to maintenance, but currently they are not frequently integrated into the planning and design of projects and rarely considered in maintenance. Planning, design and maintenance for all projects where someone could conceivably cycle should endeavor to come from a cyclists' perspective, but this can be challenging for personnel who do not cycle. Agencies should endeavor to have personnel not just drive projects, but also cycle them. If possible, it would be best to have a regular cyclist contribute to projects so that the drivers' perspective is not the only contribution through planning to design. The results also showed that aspects like location, age, and rider type did not significantly impact the most important factors in cyclists' stress or their reaction to pavement features. Although a group of humans will always vary, the most important factors to cyclists' stress and comfort appear fairly consistent across cyclists making design from a cyclists' perspective more achievable.

7.2 Limitations

As with all research endeavors, this research had some limitations. Inherently, naturalistic methods are limited in the control researchers have on the setting. This allows for very realistic experiences but can lead to large amounts of noise or unexpected events to process.

For example, the pothole that was supposed to be analyzed in CHAPTER 6 for the mixed traffic scenario was filled shortly after data collection began. There was another, less ideal, pothole along the segment, but similarly unwanted and unexpected situations can happen in any naturalistic study.

The research was also limited by a lack of high stress scenarios for the eye tracking data from Delft. This limited the ability to fully explore the impact of stress on cyclists' gaze behavior. Further data collection could remedy this but was not possible because of the Covid-19 pandemic restrictions. This limitation also highlights the difficulty of comparing a low-stress, established cycling environment such as Delft with a higher-stress, emerging cycling environment such as Atlanta. In some ways such a comparison provides interesting and valuable insights such as the finding in CHAPTER 4 that motor vehicles were the top stressor in both locations. However, the high-stress infrastructure was limited in Delft and the low-stress was limited in Atlanta, so equivalent routes were not possible.

Furthermore, eye tracking has been used so infrequently in studies of cyclists that a standard set of measures has not yet been agreed upon. Therefore, the eye tracker work in this dissertation tended to be exploratory in nature. The methods seem promising, but more work is needed to confirm the findings based on further usage of eye trackers in cyclist behavior studies. Both fixations and measures of gaze were used in these analyses, but due to the motion of the cyclist relative to the world, what would be a fixation in a static situation becomes a smooth pursuit. Eye tracking software is not well equipped to track smooth pursuits automatically. The largest dispersion value was used to try to accommodate this, but fixations were not as accurately measures as they would be in a static situation. Because of this limitation, the gaze measures would be more meaningful than the fixation measures and differences in measures of fixation would need to be more significant to be trusted. This limitation can be accommodated in some analyses, such as the work in CHAPTER 6 which used frame-by-frame analysis. These more micro-scale analyses can better correct for the software's limitations in detecting smooth pursuit movements.

One pervasive limitation was a lack of diversity in the study sample. Participants for all data collection efforts were predominately white and highly educated. Efforts were made to gather a more representative sample, especially for the online survey, but were ultimately unsuccessful. A lack of financial incentive for participation could partially explain these unsuccessful efforts, but predominately white and educated samples are a common limitation in studies on cyclists. Research is needed on how to obtain a more representative sample of the cycling population.

Furthermore, although the sample sizes in this research were large for a naturalistic cycling and eye tracking study, the sample sizes were still too small (< 30) for robust statistical analyses to be performed. Additionally, with such small sample sizes, it is impossible to be confident that the results are applicable to a larger population, thereby necessitating repeat studies to confirm the results.

7.3 Future Work

This dissertation has pointed to a few areas for future research. The results overall demonstrated the value of eye tracking, instrumented bicycles, and in-ride surveys for better understanding of cyclists and possibly other road users' stress and behavior. Future research can continue to use these methods to study road users' feelings of stress, safety, and comfort and how they behave in and interact with their environment.

The methods and data from CHAPTER 4 could be used to go a step further by incorporating the maps to better understand exactly what infrastructure existed where the cyclists commented on stressors. Additionally, these maps could be aggregated to identify stress hotspots. Furthermore, this study could be repeated in better matched cities in terms of size. Atlanta is a large city and Delft a small city, so comparison to larger Dutch cities such as Amsterdam or Rotterdam could be beneficial. Further, finding more comparable routes, if possible, could further address the limitations of this study.

The instrumented bicycle as a tool for understanding cyclist behaviors also has more potential. For example, the sonar could be used to better understand how fast vehicles are going during close-pass events and further illuminate why some close-pass events are not considered stressful. The question of cyclists' speed could also be further studied by having the same cyclist ride in separated and mixed settings. Another potential study would be to study off-peak and peak hours using these methods. Data were collected to conduct such analysis in Delft, but as a small college town, peak hour traffic and stress levels did not vary enough from off-peak hours to finish the study.

CHAPTER 5 was exploratory and opened the door to many future avenues for research. The results suggested that stress may influence gaze, but a future study with a more even distribution of stress levels on the route is needed to build more confidence in the findings. Complexity could be studied in a more controlled environment with non-visual tasks increasing the complexity. Overall, the strongest influence on gaze behavior in CHAPTER

5 was skill. Confidence in the results could be increased through further exploration with a larger sample in each skill group. Furthermore, the results suggested we cannot assume that what is known about drivers' gaze will be the same for cyclists. Little research to date has focused on cyclists' gaze behavior, but many of the studies of drivers' gaze behavior could be repeated for cyclists. In addition, a study of cyclists' gaze behavior in simulators compared to in-field could inform whether these future gaze behavior studies could be performed in the highly controlled environment of a simulator instead of in-field.

The analysis in CHAPTER 5 did not take into consideration the cyclists' speed or time series analysis, but both warrant future study. A recent paper using eye tracking data collected after that in this dissertation found that risk perception had an influence on speed and combined these had an influence on cyclists' gaze patterns (*2*). The cyclists' gaze tended to be higher and more on the travel path when cycling fast and they went slower when their risk perception was higher. Risk perception is a component of cyclists' stress, so it may also be worth looking at stress, cyclists' speed, and if they have the same relationship to gaze patterns. A validation-type study that determines the validity of fixation measurements at varying cycling speeds would also be very valuable. To the algorithm, fixations would look like smooth pursuits. The algorithm assumes the eye trackers are stationary, so the world is moving relative to the eye trackers, which can result in errors identifying fixations. Speed may impact the error resulting from this.

Another analysis method that could be used to build on this dissertation is time-series analysis. Time-series analysis in combination with areas of interest analysis has been used in a previous study of cyclists' gaze behavior to identify common gaze patterns (*3*). The paper was brief conference paper and had a narrow scope analyzing just 1 intersection.

However, it demonstrated the value of time-series analysis for identifying repetitive gaze patterns. It is possible that more stressed cyclists tend to shoulder check more frequently or very rapidly and briefly look away from the travel direction when scanning. Although the gaze area was explored in this dissertation, the use of time-series analysis could better illuminate the gaze patterns that resulted in those gaze areas.

CHAPTER 6 also suggested a couple directions for future work. This dissertation laid out the most important pavement distresses and gave ideas for incorporating the information into asset management plans. However, the next step would be to develop a model of pavement deterioration on cycle facilities. Pavement deterioration on major auto-focused assets has been extensively researched, but less is known about lower volume roads and bicycle facilities. This information is critical to asset management plans. Additionally, eye tracking can demonstrate that a cyclist has or has not fixated on an object, but it cannot definitively inform whether the cyclist has processed that information. A simulator-based study could take the research a step further to determine if the reduced fixations in mixed traffic settings are indicative that the cyclist is missing these safety-critical cues.

7.3.1 Considerations/Adjustments to the Instrumented Bicycle

In the process of this research, I identified ways in which the instrumented bicycle could be improved. The first involves redundancy. For any future data collection with the instrumented bicycle, I would recommend building in redundant components for any of the most critical sources of data. For example, I needed a redundant camera that could serve to both help identify where the cyclist was in the case of lost GPS data and provide footage if the eye tracking data were corrupted. Having redundant data allows us to make meaning out of the data even if one system has failed.

One component related to redundancy that could be valuable in future studies would be a speedometer. Speed can be derived from the GPS data, but the GPS frequently produced invalid data, likely attributable to the tall buildings in Atlanta. Building in a speedometer would allow for gathering speed data without concern around accurate/usable GPS data.

If a future study wanted to use the instrumented bicycle to look at close-pass events, it would be very valuable to have camera data that is linked to the LiDAR and Sonar data. For the inspection of close-pass events in this dissertation, I identified all close-passes, then used the timestamp to link to the GPS data, then watched the video around that location based on my knowledge of the route. Watching the video was necessary to confirm the object close to the rider was a car and not me or some other irrelevant feature. This process would be much quicker and more accurate if there were, for example, a timestamp linking the video to the LiDAR. In addition to being faster and more accurate, this method would also eliminate the risk of invalid GPS data breaking the chain.

The eye trackers were not a practical measure of stress. Extracting stress among all the other influencers of gaze was time consuming and did not come out as significant. In my opinion, the effort would not be worth the improvement over measures of stated stress. I suspect based on my experience of working with human subjects, that a button system for identifying their stress levels may be too complicated to get participants to use. I think the best option would be a microphone setup that either cues the cyclist to give a stress rating or allows them to narrate their ride. Another idea would be to use a peripheral detection task to study their mental workload. A peripheral detection task does not work with wearable eye trackers as they stand, so that would need a separate study. If eye trackers are used, it should be for a specific purpose, directly related to the research questions, and the analysis should be tested and defined prior to beginning data collection. This is heavily dependant on the intended research questions.

Other sensors that could produce value include light (lux), cadence, and brake sensors. The light sensor would add value for an eye tracking project to remove the influence of adjusting light levels on the pupillometry data. Cadence and brake sensors are frequently used in instrumented bicycle studies (*4*) and could add valuable information about the cyclists' behavior. However, I do not think these add sufficient value to change the setup to not be attachable to anyone's bike.

The choice of sensors is heavily dependent on the study being performed, so the value of each sensor and any associated trade-offs from adding it are really determined by the study itself. I strongly recommend anyone using an instrumented bicycle for research to thoroughly test every step of the research design. It is not sufficient to just test that the sensors work, but it is critical to also check the data is coming out in a usable format for your future data analyses. Thus, the way the data will be analyzed needs to be known (and tested) before the data collection protocol and sensor selection is finalized.

Finally, I have some recommendations on build and output. It is critical that the attachment mechanism to participants' bicycles is firmly holding the box in place. In this study, the box would sometimes shift sideways when a cyclist mounted/dismounted. I tried to correct this as much as possible, but the LiDAR data would be substantially more trustworthy if the box did not change position on the cyclists' bike. Additionally, because the GPS data failed sometimes, it was extremely challenging to separate files from days where multiple rides occurred. It would be much easier to manage the data if a new file were created every time the system is started.

In summary, my key lessons from using the instrumented bicycle are 1) test everything, 2) include redundancy whenever possible, and 3) the design depends on the study. A study design that has targeted research questions, has been tested through the analysis portion, and has redundancy built in for key sensors will reduce data loss and allow for smoother, more useful data analysis.

7.4 References

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APPENDIX A. US SURVEY

Seeing Like a Bicycle Study

Part A: Categorizing You as A Cyclist

To begin, we'd like to learn more about you as a cyclist. This will help us put your answers to the stress map in context.

1. How frequently do you cycle for commute/travel purposes?
   - ☐ Less than once per month
   - ☐ Several times per month
   - ☐ Several times per week
   - ☐ Nearly daily

2. How frequently do you cycle for recreation?
   - ☐ Less than once per month
   - ☐ Several times per month
   - ☐ Several times per week
   - ☐ Nearly daily

3. What type of rider would you classify yourself as?
   - ☐ Strong & Fearless – I am willing to ride my bicycle in any situation.
   - ☐ Enthused & Confident – I am confident sharing the road, but prefer bicycle facilities.
   - ☐ Comfortable, but Cautious – I am comfortable biking on most roads, but will choose another mode depending on the facilities.
   - ☐ Interested, but Concerned – I require facilities geared to cyclists to ride.

4. How long have you been biking?
   - ☐ Since childhood
   - ☐ Several years
   - ☐ One year or less
   - ☐ Just started

5. How long have you been biking in Atlanta?
   - ☐ Since childhood
   - ☐ Several years
   - ☐ One year or less
   - ☐ Just started

6. For each of the following statements, please choose the response that most closely fits your reaction.

	Strongly disagree	*Disagree*	*Neutral or No opinion*	*Agree*	*Strongly agree*
Most drivers don't seem to notice bicyclists	☐	☐	☐	☐	☐
Taking risks fits my personality	☐	☐	☐	☐	☐
I like trying things that are new and different	☐	☐	☐	☐	☐
It's pretty hard for my friends to get me to change my mind	☐	☐	☐	☐	☐
	Strongly disagree	*Disagree*	*Neutral or No opinion*	*Agree*	*Strongly agree*
I am usually very cautious with strangers	☐	☐	☐	☐	☐
I like the idea of sometimes walking or biking instead of taking the car	☐	☐	☐	☐	☐
Many bicyclists appear to have little regard for their personal safety	☐	☐	☐	☐	☐
Getting regular exercise is very important to me.	☐	☐	☐	☐	☐
I would bicycle more if my friends/family came with me.	☐	☐	☐	☐	☐
I am generally satisfied with my life.	☐	☐	☐	☐	☐

Part B: Some Background about Yourself

To help us know you a little bit better, we'd like to ask you a few background questions.

1. What is your gender identity?
   - ☐ Female
   - ☐ Male
   - ☐ Prefer not to answer
   - ☐ None of the above (please specify):__________

2. How old are you?
   - ☐ 18-24
   - ☐ 25-34
   - ☐ 35-44
   - ☐ 45-54
   - ☐ 55-64
   - ☐ 65 or older

3. Would you describe yourself as… (please check all that apply)
   - ☐ American Indian/Native American
   - ☐ Asian/Pacific Islander
   - ☐ Black/African American
   - ☐ Hispanic/Latino
   - ☐ White/Caucasian
   - ☐ Prefer not to answer
   - ☐ Other (please specify): ___________

4. Please check the category that contains your approximate annual **household income** before taxes:
   - ☐ Less than $15,000
   - ☐ $15,000 to $34,999
   - ☐ $35,000 to $54,999
   - ☐ $55,000 to $74,999
   - ☐ $75,000 to $94,999
   - ☐ $95,000 or more

5. What is your educational background? (Check highest level attained)
   - ☐ Some grade school or high school
   - ☐ High school diploma or equivalent
   - ☐ Some college, no degree
   - ☐ Associate's degree
   - ☐ Bachelor's degree
   - ☐ Graduate or professional degree

6. Approximately how many years have you lived in Atlanta? ______

7. What cities have you lived in for a substantial period of time?
   ____

8. How far do you live from your main work/school/destination? ________

Interview Questions

Instructions to interviewer: Review their map. Inquire about locations with a particularly high or low stress level

At this location, what contributed to the high/low stress rating?

General questions not tied to their map:

How familiar with this route were you? (ride segments daily, but unfamiliar with others)

What factors do you think most contributed to your stress on this route?

What factors do you think most reduced stress on this route?

Have you ever been involved in an accident while biking or with a cyclist, and how has that experience influenced your stress when biking?

Bicycle Type (to be filled out by surveyor)

Ebicycle? Y/N

Type of bicycle: ____________________________

Number of gears: _______

Tire size: ________

Seeing Like a Bicycle Study

Part A: Categorizing You as A Cyclist

To begin, we'd like to learn more about you as a cyclist. This will help us put your answers to the stress map in context. As a reminder, you may choose to not answer any question in this survey.

7. How frequently do you cycle for commute/travel purposes?
   - ☐ Less than once per month
   - ☐ Several times per month
   - ☐ Several times per week
   - ☐ Nearly daily

8. How frequently do you cycle for recreation?
   - ☐ Less than once per month
   - ☐ Several times per month
   - ☐ Several times per week
   - ☐ Nearly daily

9. What is your primary mode of transport?
   - ☐ Car
   - ☐ Bicycle
   - ☐ Motorcycle/moped
   - ☐ Public Transport
   - ☐ Walking
   - ☐ Other

10. What type of rider would you classify yourself as?
    - ☐ Strong & Fearless – I am willing to ride my bike in any situation (including mixed with motorvehicles).
    - ☐ Enthused & Confident – I am confident sharing the road with motorvehicles, but prefer bike facilities.
    - ☐ Comfortable, but Cautious – I am comfortable biking on most roads, but will choose another mode depending on the availability of bike-focused facilities.
    - ☐ Interested, but Concerned – I require bike-focused facilities to ride.

11. How long have you been biking?
    - ☐ Since childhood
    - ☐ Several years
    - ☐ One year or less
    - ☐ Just started

12. How long have you been biking in the Netherlands?
    - ☐ Since childhood
    - ☐ Several years
    - ☐ One year or less
    - ☐ Just started

13. For each of the following statements, please choose the response that most closely fits your reaction.

	Strongly disagree	*Disagree*	*Neutral or No opinion*	*Agree*	*Strongly agree*
Most drivers don’t seem to notice bicyclists	☐	☐	☐	☐	☐
Taking risks fits my personality	☐	☐	☐	☐	☐
I like trying things that are new and different	☐	☐	☐	☐	☐
It’s pretty hard for my friends to get me to change my mind	☐	☐	☐	☐	☐
I am usually very cautious with strangers	☐	☐	☐	☐	☐
I like the idea of sometimes walking or biking instead of taking the car	☐	☐	☐	☐	☐
Many bicyclists appear to have little regard for their personal safety	☐	☐	☐	☐	☐
Getting regular exercise is very important to me.	☐	☐	☐	☐	☐
I would bicycle more if my friends/family came with me.	☐	☐	☐	☐	☐
I am generally satisfied with my life.	☐	☐	☐	☐	☐

14. For each of the following statements, please choose the response that most closely fits your skill level.

	Definitely Weak	*Weak*	*Neither*	*Strong*	*Definitely Strong*
Cycling when it is slippery.	☐	☐	☐	☐	☐
Knowing how to act in particular traffic situations.	☐	☐	☐	☐	☐
Obeying traffic signals.	☐	☐	☐	☐	☐
Tolerating other road users' errors calmly.	☐	☐	☐	☐	☐
Controlling the bicycle.	☐	☐	☐	☐	☐
Adjusting speed to the conditions.	☐	☐	☐	☐	☐
Sudden braking and/or swerving when needed.	☐	☐	☐	☐	☐
Staying calm in irritating situations.	☐	☐	☐	☐	☐
Recognizing hazards in traffic.	☐	☐	☐	☐	☐
Fast reactions.	☐	☐	☐	☐	☐
Yielding to somebody else who does not have right of way.	☐	☐	☐	☐	☐
Avoiding unnecessary risks.	☐	☐	☐	☐	☐
Cycling carefully.	☐	☐	☐	☐	☐
Predicting traffic situations ahead.	☐	☐	☐	☐	☐
Maneuvering smoothly through busy traffic.	☐	☐	☐	☐	☐
Obeying traffic rules.	☐	☐	☐	☐	☐
Showing consideration for other road users	☐	☐	☐	☐	☐

15. How many accidents were you involved in as a cyclist in the last 3 years?

- ☐ 0
- ☐ 1
- ☐ 2
- ☐ 3
- ☐ 4
- ☐ 5+

16. What was the other party in the accident(s)?

- ☐ Fall
- ☐ Pedestrian
- ☐ Vehicle
- ☐ Cyclist
- ☐ Moped/Motorcycle
- ☐ Obstacle
- ☐ Other

17. Did any of your accidents with a motorized vehicle happen at an intersection?

- ☐ Yes
- ☐ No
- ☐ I was not involved in any accidents with a motorized vehicle

18. Were you involved in a collision with another cyclist when driving a motorized vehicle during the last 3 years? (Please include all accidents, regardless of how they were caused how slight they were, or where they happened)

- ☐ 0
- ☐ 1
- ☐ 2
- ☐ 3
- ☐ 4
- ☐ 5+

19. Did any of your accidents with a cyclist while driving happen at an intersection?

- ☐ Yes
- ☐ No
- ☐ I was not involved in any accidents with a motorized vehicle

Part B: Some Background about Yourself

To help us know you a little bit better, we'd like to ask you a few background questions. As a reminder, you may choose to not answer any question in this survey.

9. What is your gender identity?
   - ☐ Female
   - ☐ Male
   - ☐ Prefer not to answer
   - ☐ None of the above (please specify):__________

3. How old are you?
   - ☐ 18-24
   - ☐ 25-34
   - ☐ 35-44
   - ☐ 45-54
   - ☐ 55-64
   - ☐ 65 or older

10. Would you describe yourself as… (please check all that apply)
    - ☐ Asian/Pacific Islander
    - ☐ Black/Afro-European
    - ☐ Hispanic/Latino
    - ☐ White/Caucasian
    - ☐ Prefer not to answer
    - ☐ Other (please specify): __________

11. Please check the category that contains your approximate annual **household income** before taxes:
    - ☐ Less than €15,000
    - ☐ €15,000 to €34,999
    - ☐ €35,000 to €54,999
    - ☐ €55,000 to €74,999
    - ☐ €75,000 to €94,999
    - ☐ €95,000 or more

12. What is your educational background? (Check highest level attained)
    - ☐ Some primary school or secondary school
    - ☐ Secondary school diploma or equivalent
    - ☐ MBO/Associate's degree
    - ☐ HBO/WO/Bachelor's degree
    - ☐ Master's or PhD or advanced professional degree
    - ☐ Other __________

13. Approximately how many years have you lived near Delft? _____

14. What cities have you lived in for a substantial period of time? ____ ___________

15. How far do you live from your main work/school/destination? _______

Interview Questions

Instructions to interviewer: Review their map. Inquire about the stress levels

At this location, what contributed to the high/low stress rating?

General questions not tied to their map:

What factors do you think most contributed to your stress on this route?

What factors do you think most reduced stress on this route?

For each segment: On a scale from 1-5, 5 being extremely familiar, how familiar with this segment were you?

How have any accidents influenced your stress when biking?

What characteristics of the riding surface caused or reduced stress? Are there any locations you want to comment on specifically?

APPENDIX C. INSTRUMENTED BICYCLE LITERATURE REVIEW TABLE

Sensors						
Citation	Study Region	Research Design	Sensors	Participants /Trials	Data collection techniques in addition to sensors (such as surveys)	Topics
(Chuang, Hsu, Lai, Doong, & Jeng, 2013)	Taiwan	Quasi-naturalistic (specified route)	gps, accelerometer, gyroscope, compass, 2 ultrasonic, 8 proximity sensors, 1 variable resistor, 5 car camera black boxes	16 males, 18 female, university students, 1380 incidents	Demographics survey	Sensors, passing distance
Hu(Huertas-Leyva, Dozza, & Baldanzini, 2018)	Sweden	Naturalistic	GPS, 2 IMU (frame and handlebar), 2 brake sensors, forward facing camera; ebikes also had pedal sensor and current sensor	6 participants, 28.5 h of traditional bikes and 32.5 of e-bikes	None	Sensors, E-bikes

(Gustafsson & Archer, 2013)	Sweden	Quasi-naturalistic (specified route)	gps, forward facing camera	14 men, 4 women, 438 trips over 4910 km, 240h of cycling	Diary to record problems and events of interest for each trip	Sensors, conflicts
(Westerhuis & de Waard, 2016)	Netherlands	Naturalistic	camera forward facing, gps	17 male, 13 female, aged 50+, 20 traditional bike, 10 E-bike	Demographics survey, trip logbook	Sensors
(Gehlert et al., 2012)	Germany	Naturalistic	front and back camera, gps, wheel sensor, altimeter	55 participants, aiming to get 90, 34 male, 21 female	travel diary (start/end time, activity, secondary activity, address) and questionaire before (demographics, traits, attitudes, travel behavior, accident history) and after (behavior, changes if riding an ebike), recruitment questionaire (demographics, bike use, bike type), skills test	Sensors, age
(Gorenflo, Golab, & Keshav, 2017)	Canada	Naturalistic	GPS, gyroscope, accelerometer, magnetometer	31 university-affiliated participants (13 female), 6000 trips in total; 11 people	survey	Sensors, E0bikes

				completed all 3 surveys		
(Mackenzie, Thompson, & Dutschke, 2017)	Australia	Naturalistic	GPS, ultrasonic (2 one in front and one in back of bike), motion sensor (is the device moving)	10 riders for 2 weeks (no gender but just a test to see if it works)	None	Sensors, passing distance
(Xie et al., 2019)	China	Non-naturalistic, Variety of pavements types	forward facing camera, accelerometers (2), gps watch(2)	participant-irrelevant design, 6 pavement sections, 4 runs per section	none	Sensors
(Ambrož, 2017)	Slovenia	N/A	accelerometer, potenitometer, odometer	one rider	additional lab testing	Sensors
(Etemad, Costello, Wilson, & Wilson Page, 2016)	New Zealand	In Planning	ultrasonic, rear and forward cameras, accelerometer, gyroscope, compass, GPS	Planned	None	Sensors

(Stevenson et al., 2015)	Australia	Naturalistic	front and rear view cameras, GPS	395 to match injured cyclists in melbourne and perth, planned	cyclist crashes (Databases, hospitals)	Sensors
E-bikes						
Citation	Study Region	Research Design	Sensors	Participants /Trials	Data collection techniques in addition to sensors (such as surveys)	Topics
(Huertas-Leyva et al., 2018)	Sweden	Naturalistic	GPS, 2 IMU (frame and handlebar), 2 brake sensors, forward facing camera; ebikes also had pedal sensor and current sensor	6 participants, 28.5 h of traditional bikes and 32.5 of e-bikes	None	E-bikes, sensors
(Kovácsová et al., 2016)	Netherlands	Not naturalistic (task-based)	potentiometer, accelerometer, gyroscope, speed	30 participants (17 female) aged 30-39 and 31 participants (14 female) aged 65-79	questionnaire before (demographics, travel behavior, skill) and after (performance after), workload (peripheral detection task), and grip strength and balance test	E-bikes, age

(Langford, Chen, & Cherry, 2015)	USA	Naturalistic using bikeshare	GPS	6 traditional bike and 7 E-bikes, 2 years	None	E-bikes
(K Schleinitz, Petzoldt, Kröling, Gehlert, & Mach, 2019)	Germany	Naturalistic	forward and egocentric camera, speed sensor	88 participants (32 female, 56 male), 31 on conventional (12f, 19m), 47 pedelec (20f, 27m), 10 s-pedelec (10m), 4 weeks	None	E-bikes, conflicts
(K Schleinitz, Petzoldt, & Franke-Bartholdt, 2015)	Germany	Naturalistic	forward and egocentric camera, speed sensor	31 participants (12 female, 19 male), 28 with full data set, 4 weeks of participation, 383 h of video	Demographics survey	critical events
(Twisk et al., 2013)	Netherlands	Quasi-naturalistic (specified route)	speedometer, potentiometer, GPS, egocentric camera, accelerometer, gryroscope, compass	58 participants, 29 (18 female) aged 30-45 and 29 (13 female) aged 65+	Peripheral detection task, heart rate, helmet mounted camera, demographics survey, grip strength and balance tests	E-bikes, age

(Vlakveld et al., 2015)	Netherlands	Quasi-naturalistic (specified route)	speedometer, GPS, rotation sensor, accelerometer, steering angle sensor, egocentric camera	58 participants, 29 (18 female) aged 30-45 and 29 (13 female) aged 65+	58 participants, 29 (18 female) aged 30-45 and 29 (13 female) aged 65+	E-bikes, age
(K Schleinitz, Petzoldt, Franke-Bartholdt, Krems, & Gehlert, 2017)	Germany	Naturalistic	forward and egocentric camera, speed sensor	90 total participants, 85 used (32 female, 53 male), 28 on conventional (11f, 17m), 47 pedelec (21f, 27m), s-pedelec (9m) 4 weeks	pre-study questionnaire (demographics, travel behavior), post-study questionnaire (experience during experiment)	E-bikes
(Petzoldt, Schleinitz, Heilmann, & Gehlert, 2017)	Germany	Naturalistic	forward and egocentric camera, speed sensor	80 participants (33f, 47m), 31 conventional (12f, 19m), 49 pedelec (21f, 28m); 14,445km	pre-study questionnaire (demographics, travel behavior), post-study questionnaire (experience during experiment)	E-bikes, conflicts
(Dozza, Bianchi Piccinini, & Werneke, 2016)	Sweden	Naturalistic	Forward facing camera, GPS, 2 IMUs, 2 pressure sensors in the brake pads, pedal sensors,	12 participants (6 female), 88 critical events, 410 trips, 1474 km, 86 h of video	questionnaire (demographics, cycling habits, opinion of E-bikes), interview to understand events during experiment	E-bikes

			and current sensor			
(Boele-Vos, Commandeur, & Twisk, 2017)	Netherlands	Quasi-naturalistic (specified route)	speedometer, GPS, rotation sensor, accelerometer, steering angle sensor, egocentric camera	43 participants, 24 (15 female) aged 30-45 years, 19 (7 female) aged 65+	Peripheral detection task, heart rate, helmet mounted camera, demographics survey, grip strength and balance tests	E-bikes, age
(K Schleinitz, Petzoldt, & Gehlert, 2018)	Germany	Naturalistic	speed, GPS, forward and person facing cmaeras	32 female, 44 male; 28 traditional cyclists (11 female) and 48 pedelec (21 female)	pre-study questionnaire (demographics, travel behavior), post-study questionnaire (experience during experiment)	E-bikes
(Twisk, Platteel, & Lovegrove, 2017)	Netherlands	Quasi-naturalistic (specified route)	speedometer, GPS, rotation sensor, accelerometer, steering angle sensor, egocentric camera	30 participants (17 female) aged 30-39 and 31 participants (14 female) aged 65-79	Peripheral detection task, heart rate, helmet mounted camera, demographics survey, grip strength and balance tests	E-bikes, human control, age
(Gebhard, Golab, Keshav, & De Meer, 2016)	Canada	naturalistic	GPS, gyroscope, accelerometer, magnetometer	31 university-affiliated participants (13 female), 6000 trips	survey (travel behavior and opinions, expected E-bike use)	E-bikes

				in total; 11 people completed all 3 surveys		
(Gorenflo, Golab, et al., 2017)	Canada	naturalistic	GPS, gyroscope, accelerometer, magnetometer	31 university-affiliated participants (13 female), 6000 trips in total; 11 people completed all 3 surveys	survey (travel behavior and opinions, expected E-bike use)	Sensors, E-bikes
(Gorenflo, Rios, Golab, & Keshav, 2017)	Canada	naturalistic	GPS, gyroscope, accelerometer, magnetometer	31 university-affiliated participants (13 female), 6000 trips in total; 11 people completed all 3 surveys	survey (travel behavior and opinions, expected E-bike use)	E-bikes
(Rios, Golab, & Keshav, 2016)	Canada	naturalistic	GPS, gyroscope, accelerometer, magnetometer	31 university-affiliated participants (13 female), 6000 trips in total; 11 people completed all 3 surveys	survey (travel behavior and opinions, expected E-bike use)	E-bikes

(Lopez et al., 2017)	Belgium	naturalistic	GPS	61 participants (gender not stated), 10,008 segments, 66,440 km , 30 weeks	None	E-bikes
Passing						
Citation	Study Region	Research Design	Sensors	Participants /Trials	Data collection techniques in addition to sensors (such as surveys)	Topics
(Chuang et al., 2013)	Taiwan	Quasi-naturalistic (specified route)	GPS, accelerometer, gyroscope, compass, 2 ultrasonic, 8 proximity sensors, 1 variable resistor, 5 car camera black boxes	34 (18 female), unviersity students, 1380 passing maneuvers	Demographics survey	Sensors, passing distance
(Love et al., 2012)	USA	Naturalistic	Cameras (Parkin & Meyers)	5 (1 female), 586 passes	None	passing distance
(Mehta, Mehran, & Hellinga, 2015)	Canada	Not naturalistic, defined segments with different infrastructure	GPS, ultrasonic, camera back/left view of passing vehicles	No "participants", 27h 19 m of data, 5,227 passing maneuvers	None	passing distance

(Walker, Garrard, & Jowitt, 2014)	UK	Quasi-naturalistic, but the route was the same commute for the same person every day	Ultrasonic	No "participants", single male rider, 5690 overtaking events	survey on impression of outfits of general population (n=269)	passing distance
(Beck et al., 2019)	Australia	Naturalistic	GPS, forward facing camera, ultrasonic	60 participants (15 female), 422 trips, 5302 km, 18527 passing events	screening survey (age, gender, cycling habits, location) to purposely select participants	passing distance
(Meyers & Parkin, 2008)	UK	Not naturalistic, defined segments with different infrastructure	Side facing camera	participants irrelevant, 3 sites each with a cycle lane and no cycle lane section, no statement on trials	None	passing distance
(Parkin & Meyers, 2010)	UK	Not naturalistic, defined segments with different infrastructure	Side facing camera	participants irrelevant, 3 sites each with a cycle lane and no cycle lane section, no statement on trials	None	passing distance

(Shackel & Parkin, 2014)	UK	Not naturalistic, defined segments with different infrastructure	Cameras (side facing and forward facing), ultrasonic, microphone, speedometer	participants irrelevant but researchers kept uniform appearance, 500 overtaking instances from 25 h of video	None	passing distance
(Stewart & McHale, 2014)	UK	Not naturalistic, defined segments with different infrastructure	front and side facing camera	participants irrelevant but researchers kept uniform appearance, 14 segments ridden each way	None	passing
(Venter & Knoetze, 2013)	South Africa	Not naturalistic, defined segments with different infrastructure	ulstrasonic	participants irrelevant, 13 segments ridden each way	observer observed speeds and categorized as low medium or high	passing distance
(Dozza, Schindler, Bianchi-Piccinini, & Karlsson, 2016)	Sweden	Not naturalistic, defined segments	GPS, forward and back facing camera, LiDAR	Participants irrelevant, 84.5 km, 145 overtakings	None	passing distance
(Ithana & Vanderschuren, 2013)	South Africa	Not naturalistic, defined segments	Side facing camera	Participants irrelevant, 17 segments	None	passing distance

				ridden 4 times		
(Vanderschuren & Ithana, 2012)	South Africa	Not naturalistic, defined segments	Camera, gps, microphone	No mention	None	passing distance
(Walker, 2007)	UK	Not naturalistic; varied routes, positioning and appearance	ultrasonic sensor, video camera,laser	Participants irrelevant (1 male researcher controlling appearance), 320 km	None	passing distance
(Llorca, Angel-Domenech, Agustin-Gomez, & Garcia, 2017)	Spain	Not naturalistic, defined segments	Forward, backward, and side facing cameras; GPS; 2 lasers for speed; 2 rangefinders	professional rider, 1 mountain and 1 road bike, 2950 overtaking maneuvers	Interview on comfort	passing distance
Infrastructure Management						
Citation	Study Region	Research Design	Sensors	Participants /Trials	Data collection techniques in addition to sensors (such as surveys)	Topics

(Cleland, Walton, & Thomas, 2005)	New Zealand	Not naturalistic, various line type trials	potentiometer, accelerometer, speedometer	17 participants; 6 "inexperienced riders" rode over all 20 objects 12 times, other 11 were experienced and rode over a selection	3 tasks: target, lookback, brake; subjective evaluation of stability after ride (does braking affect stability?)	Infrastructure Management
(Walton, Dravitzki, & Cleland, 2003)	New Zealand	Not naturalistic, various line type trials	potentiometer, accelerometer, speedometer	6 participants, 15 lines 12 times	3 tasks: target, lookback, brake; subjective evaluation of stability after ride	Infrastructure Management
(Vasudevan & Patel, 2017)	India	Not naturalistic, various speed hump types	Accelerometers, on handlebars, seat, and neck (neck didn't work)	9 men, rode speed humps 15 times	Borg CR 10 Scale for discomfort	Infrastructure Management
(Galanis & Eliou, 2011)	Greece	Not naturalistic, various pavement type trials	GPS	5 (2 female), participants selected based on weight 50,60,70,80, and 90 kg	None	Infrastructure Management
(Lee, Shin, Kang, & Lee, 2016)	South Korea	Not naturalistic; defined, short trials	GPS with real time kinematics (RTK)	100 (20 women), 1200 total runs on 70 m segment	None	Infrastructure Management

(Nuñez, Bisconsini, & Rodrigues da Silva, 2018)	Brazil	Not naturalistic, various pavement type trials	Forward/down facing camera, accelerometer	Single cyclist on 5 cycle paths of various pavement types	visual inspection forms for asset inventorying	Infrastructure Management
(Neto, Viana, Braga, & Oliveira, 2018)	Brazil	Did not describe data collection	GPS, accelerometer	Did not describe data collection	None	Infrastructure Management
(Bíl, Andrášik, & Kubeček, 2015)	Czech Republic	Not naturalistic, various pavement condition trials	GPS, accelerometer	43 participants (9 women) rode 11 segments of varying pavement condition	subjective evaluation of comfort	Infrastructure Management
(Calvey, Shackleton, Taylor, & Llewellyn, 2015)	UK	Not naturalistic, various pavement condition trials	2 cameras (forward and downward facing), accelerometer, gps, speedometer (bike computer), sound meter, light meter, microphone	20 participants, 3 segments	questionnaire, totally separate from rides, about issues perceived as most important on a cycle path	Infrastructure Management
(Calvey, Taylor, Shackleton, & Llewellyn, 2013)	UK	Not naturalistic, various pavement condition trials	GPS, Forward and downward facing cameras, accelerome	pilot, just 1 rider to test sensors		Infrastructure Management

			ter, speedometer, sound meter, light meter, microphone			
(Li et al., 2015)	USA	Not naturalistic, various pavement condition trials	Accelerometer	107 participant samples across 42 road sections	various pavement texture measures, pre-survey on demographics and cycling experience, in-ride survey on comfort ratings	Infrastructure Management
Cyclist Stress						
Citation	Study Region	Research Design	Sensors	Participants /Trials	Data collection techniques in addition to sensors (such as surveys)	Topics
(Nuñez, Teixeira, et al., 2018)	Brazil	Not enough detail, likely quasi-naturalistic with defined routes	GPS, accelerometer	No info on participants, 2 routes at 2 times of day	smart band with skin conductivity levels and skin temeprature (stress measure) and GPS, noise sensor in backpack	Stress
(Feizi, Oh, Kwigizile, & Joo, 2019)	USA	Quasi-naturalistic, defined route	GPS, forward facing camera, rider body position sensor, speedomete	51 participants (10 female)	survey on comfort levels and demographics	Stress

			r, steering angle, IMU			
(Yamanaka, Xiaodong, & Sanada, 2013)	China, France, Japan	cycle tracks, bike lanes, shared, residential, shared sidewalks	Forward facing camera, lateral distance, steering, braking, accelerometer, speedometer	6 participants, 1432 trials	Survey on perceptions during the ride	Stress
(Caviedes & Figliozzi, 2018)	USA	on street (shared and bike lanes) and off-street	GPS	5 subjects with different levels of cycling experience rode route twice, 7 hours of data	Galvanic skin response (GSR) for stress, temperature from public sources, 2 helmet cameras for a 365 degree view	Stress
Conflicts						
Authors	Study Region	Research Design	Sensors	Participants /Trials	Data collection techniques in addition to sensors (such as surveys)	Topics
(Dozza & Werneke, 2014)	Sweden	Naturalistic	GPS, forward facing camera, 2 IMUs, 2 pressure sensors in the brake pads	16 participants (8 female), 2 weeks of riding, 332 trips, 1549 km, 114 h, 63 events	questionnaire on demographics and riding characteristics, interview to understand events	Conflicts

(Werneke, Dozza, & Karlsson, 2015)	Sweden	Naturalistic	GPS, forward facing camera, 2 IMUs, 2 pressure sensors in the brake pads	16 participants (8 female), 2 weeks of riding, 332 trips, 1549 km, 114 h, 63 events	questionnaire on demographics and riding characteristics, interview to understand events	Conflicts
(Petzoldt et al., 2017)	Germany	Naturalistic	Forward and egocentric camera, speed sensor	80 participants (33f, 47m), 31 conventional (12f, 19m), 49 pedelec (21f, 28m); 14,445km	pre-study questionnaire (demographics, travel behavior), post-study questionnaire (experience during experiment)	E-bikes, conflicts
(K Schleinitz et al., 2015)	Germany	Naturalistic	Forward and egocentric camera, speed sensor	31 participants (12 female, 19 male), 28 with full data set, 4 weeks of participation, 383 h of video	Demographics survey	E-bikes, conflicts
(Jahangiri, Elhenawy, Rakha, & Dingus, 2016)	USA	intersections	Forward facing and egocentric cameras, accelerometer, gyroscope, gps, speed sensor	20 participants (gender not specified)	Pre-screening to find people who pass through many intersections during their commute	Conflicts

(Katja Schleinitz et al., 2019)	Germany	Naturalistic	Forward and egocentric camera, speed sensor	88 participants (32 female, 56 male), 31 on conventional (12f, 19m), 47 pedelec (20f, 27m), 10 s-pedelec (10m), 4 weeks of participation	None	E-bikes, conflicts
(Kircher, Ahlstrom, Palmqvist, & Adell, 2015)	Sweden	Not naturalistic, various task trials	Forward and egocentric cameras	22 participants (11 female)	eye tracking, GPS (on cyclist), observers watching behavior, interviews about experience	Conflicts
(Angel-Domenech, García, Agustin-Gomez, & Llorca, 2014)	Spain	Quasi-naturalistic	GPS; forward (2), backward, and downward-side facing cameras; microphone; 2 rangefinders	2 cyclists, 648 conflicts, 10 hours of video , 130 km	subjective risk on likert scale for conflict recorded after conflict, used observations to find free flow speed	Conflicts
(Garcia, Gomez, Llorca, & Angel-Domenech, 2015)	Spain	Quasi-naturalistic	GPS; forward (2), backward, and downward-	1 cyclist (lab member), 336 meeting maneuvers,	None	Conflicts

			side facing cameras; microphone; 2 rangefinders			
(Lawrence, Oxley, Logan, & Stevenson, 2018)	Australia	Naturalistic	GPS, forward and back facing cameras	25 participants (gender not specified), 97 trips, 9h 58min, 84 km	None	Conflicts
(Gustafsson & Archer, 2013)	Sweden	Quasi-naturalistic (specified route)	gps, forward facing camera	14 men, 4 women, 438 trips over 4910 km, 240h of cycling	Diary to record problems and events of interest for each trip	Sensors, conflicts
Human Control						
Citation	Study Region	Research Design	Sensors	Participants /Trials	Data collection techniques in addition to sensors (such as surveys)	Topics
(Yizhai Zhang, Kuo Chen, & Jingang Yi, 2013)	USA	Not naturalistic, short 2 minute trials	Egocentric camera, seat force/torque sensor, handlebar strain, IMU	5 experienced riders (4 male, 1 female)	imu on rider, indoor experiments with vision-based motion capture system	human control
(Kooijman, Schwab, & Moore, 2009)	Netherlands	Quasi-naturalstic (specified route)	Egocentric camera, steer angle and steer rate, rear frame lean and yaw rate, speedomete	2 average skilled riders, 15 minute outdoor test	outside test followed by experiments in a lab setting	human control

			r, pedaling cadence			
(Twisk et al., 2017)	Netherlands	Quasi-naturalistic (specified route)	speedometer, GPS, rotation sensor, accelerometer, steering angle sensor, egocentric camera	30 participants (17 female) aged 30-39 and 31 participants (14 female) aged 65-79	Peripheral detection task, heart rate, helmet mounted camera, demographics survey, grip strength and balance tests	E-bikes, human control, age
(Ma & Luo, 2016)	Sweden	Naturalistic	GPS and altitude	11 participants (3 female), 126 trips	None	human control
(Dozza & Fernandez, 2014)	Sweden	Naturalistic	GPS, forward facing camera, 2 IMUs, 2 pressure sensors in the brake pads	16 participants (8 female), 2 weeks of riding, 332 trips, 1549 km, 114 h, 63 events	questionnaire on demographics and riding characteristics	human ctonrol
Age						
Citations	Study Region	Research Design	Sensors	Participants /Trials	Data collection techniques in addition to sensors (such as surveys)	Topics

(Kovácsová et al., 2016)	Netherlands	Not naturalistic (task-based)	potentiometer, accelerometer, gyroscope, speed	30 participants (17 female) aged 30-39 and 31 participants (14 female) aged 65-79	questionnaire before (demographics, travel behavior, skill) and after (performance after), workload (peripheral detection task), and grip strength and balance test	E-bikes, age
(Twisk et al., 2013)	Netherlands	Quasi-naturalistic (specified route)	speedometer, potentiometer, GPS, egocentric camera, accelerometer, gryroscope, compass	58 participants, 29 (18 female) aged 30-45 and 29 (13 female) aged 65+	Peripheral detection task, heart rate, helmet mounted camera, demographics survey, grip strength and balance tests	E-bikes, age
(Twisk et al., 2017)	Netherlands	Quasi-naturalistic (specified route)	speedometer, GPS, rotation sensor, accelerometer, steering angle sensor, egocentric camera	30 participants (17 female) aged 30-39 and 31 participants (14 female) aged 65-79	Peripheral detection task, heart rate, helmet mounted camera, demographics survey, grip strength and balance tests	E-bikes, human control, age
(Vlakveld et al., 2015)	Netherlands	Quasi-naturalistic (specified route)	speedometer, GPS, rotation sensor, accelerometer, steering angle sensor, egocentric camera	58 participants, 29 (18 female) aged 30-45 and 29 (13 female) aged 65+	58 participants, 29 (18 female) aged 30-45 and 29 (13 female) aged 65+	E-bikes, age

(Gehlert et al., 2012)	Germany	Naturalistic	front and back camera, gps, wheel sensor, altimeter	55 participants, aiming to get 90, 34 male, 21 female	travel diary (start/end time, activity, secondary activity, address) and questionaire before (demographics, traits, attitudes, travel behavior, accident history) and after (behavior, changes if riding an ebike), recruitment questionaire (demographics, bike use, bike type), skills test	Sensors, age
(Hatfield et al., 2017)	Australia	Naturalistic	Forward and egocentric cameras	2 control schools, 2 treatment schools, 3 students (1 female) at each school, 2 weeks of riding	None	age
Vehicle Detection						
Citation	Study Region	Research Design	Sensors	Participants /Trials	Data collection techniques in addition to sensors (such as surveys)	Topics

(Miah, Milonidis, Kaparias, & Karcanias, 2019)	England	Quasi-naturalistic (specified route)	Downward facing camera, handlebar sensors, hall effect sensor, MEMS gyroscopes and accelerometers, GPS, spatial INS	Participants Irrelevant	None	Vehicle detection
(Milonidis, Miah, Kaparias, Stirling, & Karcanias, 2017)	England	Quasi-naturalistic (specified route)	Downward facing camera, handlebar sensors, hall effect sensor, MEMS gyroscopes and accelerometers, GPS, spatial INS	Participants Irrelevant	None	Vehicle detection
(Jeon & Rajamani, 2018)	USA	Not naturalistic, controlled trials of vehicle passings	beam laser for distance	Participants Irrelevant	None	Vehicle detection

APPENDIX D. POSTHOC TESTS FOR CHAPTER 5

Table AI.1 Post Hoc Results for the X range by skill

	Motor-Tactical Skill	Mixed
Mixed	0.0003	-
Safety Motives	0.0319	0.163

Table AI.2 Post Hoc Results for the gaze area by skill

	Motor-Tactical Skill	Mixed
Mixed	0.0214	-
Safety Motives	0.00751	0.300

Table AI.3 Post Hoc Results for the fixations/second by skill

	Motor-Tactical Skill	Mixed
Mixed	0.0197	-
Safety Motives	0.0018	0.0380

Table AI.4 Post Hoc Results for the Y range by segment

	Barrier	Bumpy 1	Bumpy 2	Crossing	Curve	Low 1
Bumpy 1	0.01665		-	-	-	-
Bumpy 2	0.00658	0.9702		-	-	-
Crossing	0.00058	0.57422	0.52981		-	-
Curve	0.1639	0.1639	0.09968	0.02036		-
Low 1	0.04056	0.55683	0.45755	0.15671	0.44548	
Low 2	0.03592	0.5182	0.33349	0.12328	0.46825	0.932

Table AI.5 Post Hoc Results for the gaze area by segment

	Barrier	Bumpy 1	Bumpy 2	Crossing	Curve	Low 1
Bumpy 1	0.0045		-	-	-	-
Bumpy 2	0.0039	0.9215		-	-	-
Crossing	0.2826	0.088	0.078		-	-
Curve	0.338	0.1067	0.1356	0.9756		-
Low 1	0.025	0.5343	0.7278	0.3297	0.2873	
Low 2	0.2276	0.1268	0.1211	0.9166	0.7222	0.3779

APPENDIX E. POSTHOC TESTS FOR CHAPTER 6

Table A.1 Tukey Posthoc test results P values for perceived safety of unevenness on a sep arated facility by age (* p<0.05; ** p< 0.01 ; *** p < 0.001)

	18-24	25-34	35-44	45-54	55-64	65 or older
18-24		.953	.834	.159	.833	**.004****
25-34	.953		1.000	.431	.998	**.012***
35-44	.834	1.000		.617	1.000	**.021***
45-54	.159	.431	.617		.915	.311
55-64	.833	.998	1.000	.915		.067
65 or older	**.004****	**.012***	**.021***	.311	.067	

Table A.2 Tukey Posthoc test results P values for perceived safety of debris on a separated facility by age (* p<0.05; ** p< 0.01 ; *** p < 0.001)

	18-24	25-34	35-44	45-54	55-64	65 or older
18-24		.774	.544	.052	.775	.151
25-34	.774		1.000	.400	1.000	.546
35-44	.544	1.000		.594	1.000	.671
45-54	.052	.400	.594		.758	.997
55-64	.775	1.000	1.000	.758		.719
65 or older	.151	.546	.671	.997	.719	

Table A.3 Tukey Posthoc test results P values for perceived safety of wide cracks on a separated facility by age (* p<0.05; ** p< 0.01 ; *** p < 0.001)

	18-24	25-34	35-44	45-54	55-64	65 or older
18-24		1.000	.989	.095	.957	.271
25-34	1.000		.995	**.039***	.972	.262
35-44	.989	.995		.122	1.000	.426
45-54	.095	**.039***	.122		.584	1.000
55-64	.957	.972	1.000	.584		.692
65 or older	.271	.262	.426	1.000	.692	

Table A.4 Tukey Posthoc test results P values for perceived safety of wide cracks on a separated facility by commute frequency (* p<0.05; ** p< 0.01 ; *** p < 0.001)

	Less than 1x/month	Several x/month	Several x/week	Daily
Less than 1x/month		.138	.946	.936
Several x/month	.138		.438	**.011***
Several x/week	.946	.438		.482
Daily	.936	**.011***	.482	

Table A.5 Tukey Posthoc test results P values for comfort of wide cracks on a separated facility by recreation frequency (* p<0.05; ** p< 0.01 ; *** p < 0.001)

	Less than 1x/month	Several x/month	Several x/week	Daily
Less than 1x/month		.986	.697	.200
Several x/month	.986		.228	.057
Several x/week	.697	.228		.715
Daily	.200	.057	.715	

Table A.5 Tukey Posthoc test results P values for comfort of wide cracks on a mixed facil ity by recreation frequency (* p<0.05; ** p< 0.01 ; *** p < 0.001)

	Less than 1x/month	Several x/month	Several x/week	Daily
Less than 1x/month		.720	.834	.317
Several x/month	.720		.078	.029
Several x/week	.834	.078		.759
Daily	.317	**.029***	.759	