CPBS
Center for Pedestrian and Bicyclist Safety

A Tier-1 University Transportation Center

# Understanding External Factors and Workload's Impact on Cyclist Safety

July 2024

A Report From the Center for Pedestrian and Bicyclist Safety


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## About the Center for Pedestrian and Bicyclist Safety (CPBS)

The Center for Pedestrian and Bicyclist Safety (CPBS) is a consortium of universities committed to eliminating pedestrian and bicyclist fatalities and injuries through cutting-edge research, workforce development, technology transfer, and education. Consortium members include: The University of New Mexico; San Diego State University; The University of California Berkeley; The University of Tennessee Knoxville; and The University of Wisconsin Milwaukee. More information can be found at: https://pedbikesafety.org

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**16. Abstract**

Cycling remains a popular mode of transportation, yet cyclists face numerous safety challenges. Although human factors research typically focuses on motor vehicle drivers, studies addressing active transportation users, like cyclists, are scarce. This project aims to identify the best workload measures and devices for cycling to conduct naturalistic cycling data collection. Additionally, it aims to create a naturalistic cycling dataset considering the different workload measures identified. For that, we conducted a naturalistic cycling experiment in Albuquerque, New Mexico, with 23 volunteers riding a predetermined route while wearing various biosensors to capture performance and physiological data. Subjective workload measures were also collected using established indices from the literature. Then, the team performed exploratory analyses combining data from the multiple sensors. In these analyses, we identified differences between male and non-male riders, as well as variations in workload levels between the first and second rides, highlighting the impact of familiarity with the infrastructure. The analysis focused on two intersections in high bicycle stress segments. Results indicated that subjects preferred routes with cycle paths and good street lighting. Additionally, heart rates were higher at intersections compared to the rest of the route. Subjects tended to look straight ahead or at lower traffic light infrastructure at intersections. We conclude that combining subjective, performance, and physiological measures offers a more comprehensive understanding of the workload experienced by cyclists. These insights can inform infrastructure planning and advance methodologies for assessing bicycle stress levels, considering human factors.

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| SI* (MODERN METRIC) CONVERSION FACTORS | | | | |
|---|---|---|---|---|
| **APPROXIMATE CONVERSIONS TO SI UNITS** | | | | |
| **Symbol** | **When You Know** | **Multiply By** | **To Find** | **Symbol** |
| | | **LENGTH** | | |
| in | inches | 25.4 | millimeters | mm |
| ft | feet | 0.305 | meters | m |
| yd | yards | 0.914 | meters | m |
| mi | miles | 1.61 | kilometers | km |
| | | **AREA** | | |
| $in^2$ | square inches | 645.2 | square millimeters | $mm^2$ |
| $ft^2$ | square feet | 0.093 | square meters | $m^2$ |
| $yd^2$ | square yard | 0.836 | square meters | $m^2$ |
| ac | acres | 0.405 | hectares | ha |
| $mi^2$ | square miles | 2.59 | square kilometers | $km^2$ |
| | | **VOLUME** | | |
| fl oz | fluid ounces | 29.57 | milliliters | mL |
| gal | gallons | 3.785 | liters | L |
| $ft^3$ | cubic feet | 0.028 | cubic meters | $m^3$ |
| $yd^3$ | cubic yards | 0.765 | cubic meters | $m^3$ |
| | | NOTE: volumes greater than 1000 L shall be shown in $m^3$ | | |
| | | **MASS** | | |
| oz | ounces | 28.35 | grams | g |
| lb | pounds | 0.454 | kilograms | kg |
| T | short tons (2000 lb) | 0.907 | megagrams (or "metric ton") | Mg (or "t") |
| | | **TEMPERATURE (exact degrees)** | | |
| $^oF$ | Fahrenheit | 5 (F-32)/9 or (F-32)/1.8 | Celsius | $^oC$ |
| | | **ILLUMINATION** | | |
| fc | foot-candles | 10.76 | lux | lx |
| fl | foot-Lamberts | 3.426 | candela/$m^2$ | cd/$m^2$ |
| | | **FORCE and PRESSURE or STRESS** | | |
| lbf | poundforce | 4.45 | newtons | N |
| lbf/$in^2$ | poundforce per square inch | 6.89 | kilopascals | kPa |
| **APPROXIMATE CONVERSIONS FROM SI UNITS** | | | | |
| **Symbol** | **When You Know** | **Multiply By** | **To Find** | **Symbol** |
| | | **LENGTH** | | |
| mm | millimeters | 0.039 | inches | in |
| m | meters | 3.28 | feet | ft |
| m | meters | 1.09 | yards | yd |
| km | kilometers | 0.621 | miles | mi |
| | | **AREA** | | |
| $mm^2$ | square millimeters | 0.0016 | square inches | $in^2$ |
| $m^2$ | square meters | 10.764 | square feet | $ft^2$ |
| $m^2$ | square meters | 1.195 | square yards | $yd^2$ |
| ha | hectares | 2.47 | acres | ac |
| $km^2$ | square kilometers | 0.386 | square miles | $mi^2$ |
| | | **VOLUME** | | |
| mL | milliliters | 0.034 | fluid ounces | fl oz |
| L | liters | 0.264 | gallons | gal |
| $m^3$ | cubic meters | 35.314 | cubic feet | $ft^3$ |
| $m^3$ | cubic meters | 1.307 | cubic yards | $yd^3$ |
| | | **MASS** | | |
| g | grams | 0.035 | ounces | oz |
| kg | kilograms | 2.202 | pounds | lb |
| Mg (or "t") | megagrams (or "metric ton") | 1.103 | short tons (2000 lb) | T |
| | | **TEMPERATURE (exact degrees)** | | |
| $^oC$ | Celsius | 1.8C+32 | Fahrenheit | $^oF$ |
| | | **ILLUMINATION** | | |
| lx | lux | 0.0929 | foot-candles | fc |
| cd/$m^2$ | candela/$m^2$ | 0.2919 | foot-Lamberts | fl |
| | | **FORCE and PRESSURE or STRESS** | | |
| N | newtons | 0.225 | poundforce | lbf |
| kPa | kilopascals | 0.145 | poundforce per square inch | lbf/$in^2$ |

# Understanding External Factors and Workload's Impact on Cyclist Safety

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## Acronyms, Abbreviations, and Symbols

| | |
|---|---|
| ACS | American Community Survey's |
| ANS | Autonomous Nervous System |
| AOIs | areas of interest |
| BLOS | Bicycle Level of Service |
| BLTS | Bicycle Levels of Stress |
| BPM | Beats per Minute |
| CAS | Cycling Anger Scale |
| CAX | Cycling Anger Expression Inventory |
| CBQ | Cyclist Behavior Questionnaire |
| CDC | Centers for Disease Control and Prevention |
| CNC | Computerized Numerical Control |
| DOT | Department of Transportation |
| ECG | Electrocardiogram |
| EDA | Electrodermal Activity |
| EEG | Electroencephalogram |
| EMG | Electromyography |
| FFMQ | Five Facet Mindfulness Questionnaire |
| GSR | Galvanic Skin Response |
| HF | High Frequency |
| HF | Human Factors |
| HR | Heart Rate |
| HRV | Heart Rate Variability |
| IBIs | Inter Beat Intervals |
| IPIP | International Personality Item Pool |
| LF | Low Frequency |
| LTS | Levels of Traffic Stress |
| MAAS | Mindfulness Attention and Awareness Scale |
| MV | Mental Workload |
| RMSSD | Root Mean Squared Differences. |
| RPE | Borg's Perceived Exertion and Pain Scales |
| RSME | Rating Scale Mental Effort |
| SLMs | Shared Lane Markings |
| SWAT | Subjective Workload Assessment Technique |
| TLX | Task Load Index |
| VR | Virtual Reality |
| WSL | Washington State Legislature |

## Abstract

Cycling remains a popular mode of transportation, yet cyclists face numerous safety challenges. Although human factors research typically focuses on motor vehicle drivers, studies addressing active transportation users, like cyclists, are scarce. This project aims to identify the best workload measures and devices for cycling to conduct naturalistic cycling data collection. Additionally, it aims to create a naturalistic cycling dataset considering the different workload measures identified. For that, we conducted a naturalistic cycling experiment in Albuquerque, New Mexico, with 23 volunteers riding a predetermined route while wearing various biosensors to capture performance and physiological data. Subjective workload measures were also collected using established indices from the literature. Then, the team performed exploratory analyses combining data from the multiple sensors. In these analyses, we identified differences between male and non-male riders, as well as variations in workload levels between the first and second rides, highlighting the impact of familiarity with the infrastructure. The analysis focused on two intersections in high bicycle stress segments. Results indicated that subjects preferred routes with cycle paths and good street lighting. Additionally, heart rates were higher at intersections compared to the rest of the route. Subjects tended to look straight ahead or at lower traffic light infrastructure at intersections. We conclude that combining subjective, performance, and physiological measures offers a more comprehensive understanding of the workload experienced by cyclists. These insights can inform infrastructure planning and advance methodologies for assessing bicycle stress levels, considering human factors.

## Executive Summary

Cycling remains a popular mode of transportation, yet cyclists face numerous safety challenges. Although human factors research typically focuses on motor vehicle drivers, studies addressing active transportation users, like cyclists, are scarce. This project's primary objective was to recognize workload measures that could help analyze cyclists' behavior. For that, we first conducted an extensive literature review that resulted in a published paper. Additionally, we conducted a naturalistic cycling experiment involving 23 cyclists in Albuquerque, New Mexico. Using wearable biosensors such as electrocardiogram (ECG) and eye-tracking devices, we collected subjective, physiological, and performance data in a real-world setting. The data collection process consisted of three phases. During the initial phase, participants are asked to provide information on their travel behaviors and various sociodemographic factors through a survey. In the second phase, they wore various biosensors and completed rides in both clockwise and counterclockwise directions. In the third phase, subjects were given another questionnaire using recognized workload scales, such as the NASA TLX and Borg RPE scales, among others. The route, approximately 1.4 miles long, started and ended at the Lobo Bike Shop on the University of New Mexico campus and included various bike infrastructure types and intersections.

Our sample consisted of 70% male volunteers, which aligns with the percentage of male cyclists in the U.S. The average age of male subjects was 33 years, while the average age of non-male subjects was 27.7 years. This demographic distribution also reflects national cycling trends and commuter biker statistics in Albuquerque. Statistical analysis using the 2022 American Community Survey's 5-year estimate indicated no significant difference between our sample and the population regarding gender distribution when combining non-binary and female categories. The age distribution showed no significant difference for individuals younger than 24. However, there was a significant difference for those aged 25 and older, with most participants falling between 25 and 44 years old, compared to 44% of bike commuters in Albuquerque. In terms of ethnicity, 56% identified as Hispanic or Latino, 52% as Caucasian or White, 13% as Asian, and 34.74% as Other. On average, participants lived in households with 2.1 inhabitants and reported fewer bike crashes compared to car crashes over the past three years.

Participants primarily commuted by bike to work or school but preferred using a car for grocery shopping, personal errands, and social recreation. Using the various scales considered in the questionnaires, subjects revealed a high likelihood of using routes with cycle paths or marked lanes at crossings, good street lighting, smooth surfaces, minimal traffic, and signalized crossings. Participants were extremely unlikely to use the fastest route. They felt highly successful in accomplishing the task, which was more mentally demanding than physically demanding, by responding to the NASA TLX scale. The internal consistency of the scales used was acceptable, with Cronbach's alphas between 0.72 and 0.78. Subjective measures captured cultural and socioeconomic factors influencing route planning and decision-making. Limitations include the inability to capture moment-to-moment data without disrupting the naturalistic setting.

When combining the measures, we found that reported mental workload, based on NASA TLX stress levels, indicated that higher stress levels did not correlate with significantly higher BPM captured by ECG. We also observed that the mean BPM was generally above the overall session average at intersections, with exceptions at the Girard and Silver intersections depending on the stated stress levels and ride direction. BPM fluctuations at intersections for individual subjects highlighted increased stress or physical exertion compared to other parts of the route. Finally, heat maps showed that cyclists predominantly focused straight ahead at intersections, with males having narrower areas of focus compared to non-males, who looked further into intersections. Additionally, the area of interest expanded for cyclists on their second ride, suggesting increased familiarity and comfort with the route.

This data collection left many lessons learned. For instance, careful planning ensured the selection of suitable sensors and processing software was key. Unexpected issues, such as a malfunctioning GPS, were mitigated using backup devices. Additionally, ensuring participants understood the experiment's procedures was crucial. As future research, we believed integrated biosensors could minimize interference and improve data collection.

The conclusions of this study emphasize the importance of a holistic approach to understanding cyclists' experiences. By integrating subjective, physiological, and eye-tracking data, we gained a comprehensive understanding of these experiences, revealing gender differences in visual attention patterns that necessitate further research to enhance cycling safety. The insights derived from this study have practical applications, such as informing safer and more efficient road design, optimizing training, identifying stress triggers, and monitoring safety and health. Future research leveraging advanced technologies and naturalistic study designs can further develop comprehensive assessments of cyclist workload and safety. This project also allowed the students involved to gain an understanding of human factors science in transportation and initiated knowledge at UNM regarding the use of biosensors in active transportation. Additionally, the findings have policy implications, guiding the development of safer cycling environments and promoting active transportation and public health. This study underscores the critical need for a holistic approach to improve cycling infrastructure and safety for all.

# Introduction

Cyclists are vulnerable road users; nearly 1000 cyclists lose their lives, and 130,000 are injured annually on US roads (CDC, 2022). Unfortunately, the number of cyclist fatalities has witnessed an upward trend between 2012 and 2018 (Venkatraman et al., 2021), with the majority of fatalities happening in urban settings (78%) and during daylight (49%) (NHTSA, 2019). These numbers are projected to increase with the expansion of active transportation infrastructure and adoption of Complete Streets policies in various U.S. cities and states if no serious steps are taken to improve the current safety situation (Smart Growth America, 2023; U.S. DOT, n.d.; WSL, 2022).

"Human Factors" is the science that explains the relationship between machines and users, and mental workload is a usual quantification metric (Tignor, 2022). Key aspects of human factors science include human performance, safety, human-infrastructure interaction, and additional relevant factors. However, research on human factors in transportation typically concentrates on motor vehicle drivers, often neglecting active transportation users like cyclists. Cyclists might face higher workload levels due to their vulnerability compared to car drivers and the changing workload from physical activity (increased fatigue with cycling), direct exposure to the surrounding environment (e.g., weather conditions), and issues related to disconnected infrastructure. Hence, it is essential to understand the factors impacting cyclists' mental workload to improve their comfort, safety, and infrastructure planning.

Cyclists are among the most vulnerable users in the transportation system, lacking the protection provided by vehicle bodies, safety features such as airbags, or reliance on engines (Schwab & Meijaard, 2013). They have to exert physical effort, which causes fatigue and consequently consumes the attentional resources of the cyclists—knowing that cyclists' physical supply is influenced by the broad spectrum of capabilities of cyclists (elders vs. young, tall vs. short, male vs. female, overweight vs. slim, etc.). Moreover, cyclists are more vulnerable to their surrounding environment than drivers, yet motor vehicular infrastructure guidelines often overlook their specific needs and safety concerns. This discrepancy is further amplified by a lack of data, which is the foundation for developing comprehensive guidelines prioritizing cyclists' safety and comfort. Consequently, the need for more research and guidelines becomes evident.

Cycling infrastructure vulnerability is represented by the discontinuity of infrastructure, maintenance issues (snow plowing, etc.), and the necessity of sharing infrastructure with other road users such as cars, trucks, and mass public transportation. Even in comparison with pedestrians, cyclists are more exposed to conflicts and crashes because they interact with vehicular traffic explicitly, not only at intersections. Also, cyclists travel longer distances at higher speeds than pedestrians with higher restricted movements, such as shoulder checks. In brief, all those factors that cause the vulnerability of cyclists would also impact cyclists' mental workload, perception, comfort, and behavior. Recently, advancements in the availability and portability of sensors have significantly improved data collection capabilities. These sensors can gather a wide variety of data, including speed for performance measures, electrocardiogram (ECG) and electrodermal activity (EDA) for stress measurements, and eye tracking for assessing gaze behavior, among other metrics.

Currently, various state Department of Transportation (DOTs) are requiring the use of Bicycle levels of stress (BLOS) in the design of bicycle infrastructure on state roads by using pre-defined methodologies, especially those designed using secondary sources (ODOT, 2024; WSDOT, 2023). While BLOS has been instrumental in advancing our understanding of bicycling suitability, there is a growing need to evolve these methodologies. By leveraging naturalistic studies and advanced technologies, we can develop more comprehensive and accurate assessments of BLOS, ultimately creating safer and more enjoyable cycling environments for all user profiles.

Despite the limited literature on human factors in cycling, this project aims to address this research gap by presenting a comprehensive review of the factors affecting cyclists' workload, perception, and behavior. It explains various workload measures and evaluates their effectiveness in quantifying cyclist workload. Additionally, it conducts a naturalistic cycling experiment to create a database, and explores the collected workload measures, considering the diversity of the sample and various infrastructural contexts. In this project, variable infrastructure will be considered in terms of two intersections in the experiment. To achieve these research objectives, a scoping review was carried out using the methodological framework proposed by (Arksey & O'Malley, 2005). Additionally, we collected subjective, performance, and physiological measures from respondents in Albuquerque, New Mexico, along a defined route. Albuquerque serves as an important case study for this project due to its diverse urban landscape and varying infrastructure quality. Statistics indicate that Albuquerque experienced 0.71 cyclist fatalities per 100K in 2020, representing 3.8% of all roadway fatalities, making it imperative to understand the human factors contributing to safety risks in this region. Additionally, Albuquerque's commitment to promoting cycling through dedicated bike lanes and trails offers valuable insights into the impact of infrastructure on cyclist behavior and safety, addressing a crucial aspect of this study. Finally, we concluded by discussing the findings and providing venues for future work.

## Literature Review

The literature review covers a wide range of topics relevant to the study. It begins with exploring factors influencing perception, workload, and behavior. Following this, an examination of various types of workload measures is conducted, accompanied by a brief overview of specific methodologies for their quantification. Subsequently, the discussion shifts to the advantages of naturalistic experiments for non-motorized users, highlighting their importance within the scope of this research. It should be noted that sections of this literature review have been previously published (Habib et al., 2024) as part of the outcomes of this project.

### Factors Impacting Perception, Workload, and Behavior

During cycling, cyclists allocate their cognitive resources to various challenging characteristics that consume the cyclists' workload supply. The workload relates to but is not limited to 1) the characteristics of cyclists (age, sex, personality, etc.), 2) adapting to infrastructural design changes (longitudinal grades), 3) interpreting external information (signing, traffic devices, marking, type/quality of the route, obstacles, and hazards, portable devices, etc.), 4) type of bicycle (assisted vs. conventional), 5) changing decisions due to weather, and several other factors. In this literature review, we will describe characteristics within the first four situational characteristics groups and also review how human factors have been studied in relationship to the mental workload of motor vehicle drivers.

#### Age Impacts

Age is a significant factor in expressing cyclists' physical perceptions, capabilities, and decisions. For instance, children were found to have delayed reaction times compared to adults regarding identifying hazards, suggesting that hazard perception depends on age and experience (Zeuwts et al., 2017). Similarly, perceptions of infrastructure differed between older and younger cyclists. Older cyclists desired more cycle paths than younger cyclists, with more strict respect for laws, because it made them feel safer (Bernhoft & Carstensen, 2008). Similar conclusions arise when studying workload. A study examining middle and older age participants found that, regardless of bicycle type (assisted or conventional), workload levels increased with age in complex situations such as when making left turns (Boele-Vos et al., 2017). Moreover, a study found that using portable devices reduced cognitive resources for teenage and young adult cyclists, increasing the likelihood of collisions. Additionally, the complexity of the cycling traffic situation was identified as a predictor of crashes (Bulsink et al., 2016). It was also found that older adults take longer to recover from perturbations. The results revealed that older cyclists rely more on knee movement to keep balance than younger subjects. This counter behavior explains the increased risk of older cyclists in single-sided (tip-over) bicycle accidents (Afschrift et al., 2022). Those findings were confirmed by the results of another study where older cyclists use different strategies than younger cyclists in rebalancing themselves after perturbations. Movement limitations consume attentional resources that may lead to errors and, as a result, involvement in collisions (Allum et al., 2002). The studies reviewed herein allow us to conclude that age, workload, and cycling traffic complexity significantly impact cyclist safety and could affect future behaviors. Studies on behaviors revealed that using portable devices has dissimilar impacts on different age groups' behavior (Goldenbeld et al., 2012). Additionally, mental impairments in relation to age were associated with cyclists' safety, represented by falling off (Engbers et al., 2018). Overall, cyclist's perceptions, workload, and behaviors are differentially affected by the cyclist's age; however, other situational characteristics might contribute too.

### Infrastructure

Infrastructure characteristics also heavily impact cyclists' perceptions, workload levels, and behavior. Similar to age, specific movements, traffic complexity, and infrastructure availability have been studied in their context. In terms of perceptions, a study using an online survey in 20 countries revealed strong associations between infrastructure, self-reported crashes, and human factors regardless of the respondent's background (Useche et al., 2018). In terms of workload levels, qualitative and quantitative workload measures have been developed to evaluate cyclists' feelings of comfort and safety. A study used subjective and physiological workload measures to assess the infrastructural impact on cyclists' workload, concluding that quantitative expression of cycling workload is crucial for safe bikeway design and management and controlling conditions that induce overworking and user discomfort (S. Qu et al., 2022). Similarly, a study used workload physiological measures and video recordings to understand the influence of infrastructural settings on cyclists, concluding that stress levels increase while cycling in mixed traffic settings and peak traffic times (Caviedes & Figliozzi, 2018). The quality of the cycling path itself was also found to consume cyclists' workload supply, which may impact the alertness and responsiveness of cyclists to surrounding environmental hazards (Vansteenkiste et al., 2014). Regarding behavior, results have agreed that cyclists' behavior changes with proximity to motorized vehicles (Chuang et al., 2013). Using Virtual Reality (VR), a study concluded that cyclists' speeds changed depending on the bike facility, showing more braking and head movements close to intersections, while average speed increased when cycling in segregated lanes, where cyclists felt the safest (Nazemi et al., 2018). In a different study regarding the impact of mixed and separated bike lanes on cyclists' workload (Knight & Charlton, 2022), separated bike lanes were generally considered safer due to the absence of interaction with vehicular traffic. However, cyclists suffer/enjoy a low mental workload (mental fatigue) while cycling in separated bike lanes, which may increase collisions due to increased speed or low perception of hazards.

### Portable Devices

Portable devices, such as smartphones, tablets, and headphones, represent a significant reason for cyclists' impairments, and, as a result, changes in workload levels and behaviors lead to a shortage of cognitive resources and errors. A study found a higher chance of getting involved in a crash for teens while using portable devices versus the same age group that does not use portable electronic devices (Goldenbeld et al., 2012). Similarly, male students' mobile phone usage during cycling was associated with experiencing a crash/near crash. Interestingly, the perception of risk among those students helped them decrease mobile phone usage, consequently improving cyclists' safety (Ichikawa & Nakahara, 2008). Another study found through a questionnaire that cyclists hardly or never engaged in secondary tasks such as using mobile phones due to the perceived risk in the cycling infrastructure (Young et al., 2020). Regarding workload, various studies have agreed that using portable devices increases mental effort ratings. Among all activities, texting on the phone was found to have the highest negative impact on cyclists' performance (de Waard et al., 2010). Talking or texting was argued to contribute to risky behavior by cyclists that resulted in fall-off collisions. Texting was the most impacting among different distractions, even more than listening to music. Texting was translated into a mental load that resulted in speed reduction, increased acceleration, and changes in the cycling deflection angle (Jiang et al., 2021). Hence, using portable devices could have profound implications on cyclist workload, often translated into risky behaviors (Jiang et al., 2021; Santos-Reyes et al., 2023).

### Bicycle Type

Researchers have studied the impact of assisted bicycle on cyclists' workload, as they differ from conventional bicycles by providing higher cycling speeds. For example, e-bikes can influence cyclists' perception, decrease fatigue and affect their behavior. Additionally, e-bikes can also influence car drivers' behavior and judgment in yielding situations, potentially affecting cyclists' maneuverability and perception in hazardous situations. Regarding workload, mental workload, and anxiety levels were captured from volunteers riding e-bikes equipped with sensors to monitor and record speed, bike balance, and the proximity of cars overtaking bicycles (Pejhan et al., 2021). The results indicated a significant speed difference between e-bikes and conventional bicycles, which did not impact the perception of cyclists (maybe because of the difference in cycling situations); however, high levels of workload and anxiety were detected when cyclists tried to overtake slow cars in both bike types. These results were consistent with those from another study, where middle-aged and older cyclists' workload was similar in e-bikes and conventional bicycles (Twisk et al., 2013). Regarding behaviors, a study that captured subjective measures indicated a higher likelihood of collisions requiring emergency department treatment than conventional bicycles when riding e-bikes (Schepers et al., 2014). Similar results were identified in another study; e-bike riders achieved higher average speeds, accelerations, and breaking, which increased their need for emergency department treatment (Huertas-Leyva et al., 2018). Other studies confirmed the increase in speed of cyclists on e-bikes in comparison with conventional bicycles, potentially increasing risky behaviors (Dozza et al., 2016; Jenkins et al., 2022).

### Car Driver Workload

The proximity of cyclists has been shown to impact drivers' workload and behavior. In a simulation study, a peripheral detection task was used for workload measurement of car drivers at intersections during the presence and absence of cyclists (Vlakveld, 2011). The results indicated that compared to intersections without cyclists, drivers reduced speed with more substantial deceleration and shorter distances, knowing that drivers have the right-of-way, especially at rural intersections. This could be attributed to the expectancy of drivers regarding cyclists' unexpected actions, which represents an underlying latent hazard (Kaya et al., 2021). An eye-tracker was used at urban intersections to examine the visual scanning failures at conflict points with cyclists (O'Hern et al., 2019). After analyzing 443 turn events, the results concluded that scanning failures were 2.01 times more significant for drivers without cycling experience. Similarly, a study revealed that car drivers' eye fixation time on cyclists (in the opposite and same direction) was the highest right after eye fixation time on the cockpit (Bongiorno et al., 2017). Fixation time on cyclists in the same direction was higher than fixation time on cyclists in the opposite direction, and this could be explained by the expectation of cyclists' sudden movements. These results confirmed the increased workload levels of car drivers when they are close to cyclists (Bongiorno et al., 2017). Additionally, the geometric design impacted the drivers' behavior when overtaking cyclists (Bella & Silvestri, 2017). In a simulator study, lateral clearance and speed reductions were captured to understand the impact of road curvature and direction of curvature on car drivers' behaviors. A minor clearance was recorded on tangential sections with no speed reductions. Higher clearances were observed on the right- and left curves, where speed reduction occurred on the right curves but speed increase on the left curves.

Perceptions, workload, and behaviors in the interaction between car drivers and cyclists are better understood from the motor vehicle driver than from the cyclist aspect. Although the aforementioned factors might influence cyclists' workload, little research is dedicated to measuring it from the cyclist's perspective. Hence, identifying which measures could be used to understand cyclist workload is a timely research endeavor. Based on the studies presented about human factors and workload measures, Table 1 offers a summary of studies on cycling behavior, perception, and workload.

**Table 1. Summary of Human Factor Studies**

| Factors Measured | Test Name or Target Measure | | | Studies Set-ups |
|---|---|---|---|---|
| | **Subjective** | **Performance** | **Physiological** | |
| **Age** | Study-specific survey<br>(Goldenbeld et al., 2012) | Peripheral detection task<br>(Boele-Vos et al., 2017; Zeuwts et al., 2017)<br>Average cycling speed<br>(Boele-Vos et al., 2017)<br>Steering rotation<br>(Afschrift et al., 2022; Bulsink et al., 2016) | | Survey<br>(Bernhoft & Carstensen, 2008; Engbers et al., 2018; Goldenbeld et al., 2012)<br>Field Experiment<br>(Boele-Vos et al., 2017)<br>Laboratory Experiment<br>(Afschrift et al., 2022; Allum et al., 2002; Bulsink et al., 2016; Zeuwts et al., 2017) |
| **Infrastructure** | *Mental Workload:*<br>Study-specific survey<br>(Knight & Charlton, 2022; Nazemi et al., 2018; Useche et al., 2018)<br>Task Load Index (TLX)<br>(S. Qu et al., 2022)<br>Cooper–Harper scale<br>(S. Qu et al., 2022)<br>Subjective Workload Assessment Technique (SWAT) (S. Qu et al., 2022)<br>*Physical Workload:*<br>Borg's Perceived Exertion and Pain Scales (RPE)<br>(S. Qu et al., 2022) | Peripheral detection task<br>(S. Qu et al., 2022)<br>Braking<br>(Nazemi et al., 2018)<br>Speed<br>(Nazemi et al., 2018) | Heart rate variability<br>(Nazemi et al., 2018; S. Qu et al., 2022)<br>Head movement<br>(Knight & Charlton, 2022)<br>Gaze Behavior<br>(Vansteenkiste et al., 2014)<br>Galvanic skin response<br>(Caviedes & Figliozzi, 2018) | Survey<br>(Knight & Charlton, 2022; Useche et al., 2018)<br>Field Experiment<br>(Caviedes & Figliozzi, 2018; Chuang et al., 2013; S. Qu et al., 2022; Vansteenkiste et al., 2014)<br>Virtual Reality Simulator<br>(Nazemi et al., 2018) |

| Factors Measured | Test Name or Target Measure | | | Studies Set-ups |
|---|---|---|---|---|
| | **Subjective** | **Performance** | **Physiological** | |
| **Portable Devices** | Study-specific survey (de Waard et al., 2010; Goldenbeld et al., 2012; Ichikawa & Nakahara, 2008; Santos-Reyes et al., 2023)<br>Rating Scale Mental Effort (RSME) (de Waard et al., 2010)<br>Mindfulness Attention and Awareness Scale (MAAS) (Young et al., 2020)<br>Five Facet Mindfulness Questionnaire (FFMQ) (Young et al., 2020)<br>Cycling Anger Scale (CAS) (Young et al., 2020)<br>Cycling Anger Expression Inventory (CAX) (Young et al., 2020)<br>Cyclist Behaviour Questionnaire (CBQ) (Young et al., 2020)<br>International Personality Item Pool (IPIP) Big-Five Factor Markers (Young et al., 2020) | Peripheral detection task (de Waard et al., 2010)<br>Speed (de Waard et al., 2010) | | Survey (de Waard et al., 2010; Ichikawa & Nakahara, 2008; Santos-Reyes et al., 2023; Young et al., 2020)<br>Observational Experiment (de Waard et al., 2010)<br>Field Experiment (de Waard et al., 2010; Jiang et al., 2021) |

| Factors Measured | Test Name or Target Measure | | | Studies Set-ups |
|---|---|---|---|---|
| | **Subjective** | **Performance** | **Physiological** | |
| **Bicycle Type** | Study-specific survey (Schepers et al., 2014) | Peripheral detection task (Pejhan et al., 2021; Twisk et al., 2013)<br>Braking (Dozza et al., 2016; Huertas-Leyva et al., 2018; Twisk et al., 2013)<br>Steering rotation (Dozza et al., 2016; Twisk et al., 2013)<br>Speed (Twisk et al., 2013) | Heart rate variability (Pejhan et al., 2021; Twisk et al., 2013)<br>Head movement (Twisk et al., 2013) | Survey (Schepers et al., 2014)<br>Field Experiment (Pejhan et al., 2021; Twisk et al., 2013)<br>Naturalistic Study (Dozza et al., 2016; Huertas-Leyva et al., 2018) |
| **Car Drivers Workload** | Rating Scale Mental Effort (RSME) (O'Hern et al., 2019) | Peripheral detection task (O'Hern et al., 2019; Vlakveld, 2011)<br>Braking distance (Vlakveld, 2011)<br>Steering rotation (Bongiorno et al., 2017)<br>Speed (Bella & Silvestri, 2017; O'Hern et al., 2019; Vlakveld, 2011) | Gaze behavior (Bongiorno et al., 2017; Kaya et al., 2021)<br>Galvanic skin response (Bongiorno et al., 2017) | Driving Simulator (Bella & Silvestri, 2017; O'Hern et al., 2019; Vlakveld, 2011)<br>Field Experiment (Bongiorno et al., 2017; Kaya et al., 2021) |

## Workload Measures

The process of quantifying cyclists' human factors is complex due to the many interfering factors that impact cyclists' workload, making workload multidimensional. The overview presented in the previous section shows that factors range from interference with the primary task (cycling) to others, such as demographic characteristics of the cyclist, experience in cycling and other modes, traffic laws, and many others. Due to these factors' diverse and interactive nature, it is *not recommended* to measure their individual contributions to cyclists' cognitive resources using a single measure. Generally, workload measures are classified as 1) subjective, 2) performance, and 3) physiological, which have been extensively used to evaluate users' workload in various environments such as aviation, driving, and nuclear plants (Tao et al., 2019).

However, cycling workload levels are unique in nature because of the strong interaction with the physical workload, interaction with other road users, changing and discontinued infrastructure, and other factors that cause the workload levels to fluctuate. In addition, it is worth mentioning that a physical workload interferes with the cyclists' mental workload, reflected in errors and wrong decisions (Boksem & Tops, 2008). Mental or cognitive fatigue – not to be confused with physical fatigue- results from underloading (monotony or wealth of resources that causes boredom) or overloading without rewards (Boksem & Tops, 2008; Hockey, 2013; Irvine et al., 2022; Jaquess et al., 2017; Lal & Craig, 2001), which has also been noted to interfere with cognitive performance (Pageaux & Lepers, 2018; Paxion et al., 2014; Pires et al., 2018). In connection, there is a strong association between mental workload and physical workload, as once the available attentional resources are consumed, the performance deteriorates, leading to task failure (Boksem & Tops, 2008; Jaquess et al., 2017). This occurs because the brain regions responsible for sensing effort are also involved in cognitive fatigue and exertion (Irvine et al., 2022). As a result, the physical effort diminishes the resources available and used for mental workload (Boksem & Tops, 2008; Pires et al., 2018). In the following subsections, we will summarize in a broad sense the three different workload measures available.

### Subjective Workload Measures

Subjective workload measures are the most common measures in the literature. Subjective measures are advantageous because they are economically feasible, do not require sophisticated measurements, and are non-intrusive. In various studies, subjective workload measures do not follow a specific, pre-validated questionnaire but rather are efforts from the authors to understand the impacts of factors such as infrastructure (Knight & Charlton, 2022; Nazemi et al., 2018; Useche et al., 2018), the use of portable devices while riding (Goldenbeld et al., 2012; Ichikawa & Nakahara, 2008; Santos-Reyes et al., 2023), previous cycling experience (Schepers et al., 2014), in cyclist workload. Many other studies do however use pre-determined subjective measures to understand user systems' workload. The NASA TLX (Hart & Staveland, 1988), the Borg-CR10 scale (Borg, 1982), and RSME (de Waard et al., 2010) are examples of common subjective scales. However, it is worth mentioning that subjective workload measures are unidimensional (unlike NASA TLX that is multidimensional) in nature, which does not perfectly fit the outdoor cycling environment (Paxion et al., 2014). Subjective workload measures are also prone to respondents' bias (Annett, 2002). The results also must be accompanied or validated by other workload measures. For instance, subjective workload measures in the work environment have resulted in differential outcomes according to cultural differences (Johnson & Widyanti, 2011). Hence, understanding subjective workload measures for cyclists might not look like a one-size-fits-all approach; careful considerations are necessary to quantify subjective workload.

### Performance Workload Measures

Performance measures have been used extensively in assessing car drivers' workload levels. Usually, the performance measures target the primary and the secondary tasks. For instance, primary tasks in driving involve lane control, lateral changes in car trajectory, headway, speed choice, and more. Secondary tasks, on the other hand, refer to those that interfere with the primary task. Typically, peripheral detection tasks are employed to measure the attentional resources consumed by the primary task (Tao et al., 2019). Choosing the proper performance workload measure in cycling is challenging and should be totally segregated from car driving tasks' workload measures. For instance, while speed choice and its variability are commonly used to investigate workload for car drivers, cycling speed cannot be reliably used as a workload measure due to the influence of cyclists' behavior. Cyclists might not stop completely or dismount, fearing a loss of stability at stop signs, which demonstrates an example where behavior significantly impacts performance measures (Schwab & Meijaard, 2013). Another example is headway, an appropriate measure for motor vehicles but holds less significance for bicycles due to their lower volumes.

### Physiological Workload Measures

Physiological measures serve as objective workload indicators, and their usage has experienced significant growth thanks to advancements in sensor development and production (Tao et al., 2019). They include electroencephalogram (EEG), electromyography (EMG), electrocardiogram (ECG), respiratory rate, and electrodermal activity (EDA). EEG is frequently employed for measuring workload in aircraft pilots, but it has the disadvantage of being susceptible to influences from factors unrelated to workload (Secerbegovic et al., 2017; Taheri Gorji et al., 2023). However, cardiovascular measures, such as heart rate, blood pressure, and respiration, are also the most studied in workload studies (Tao et al., 2019). Heart rate is sensitive to workload changes but is impacted by emotions, physical effort, respiration, and other factors such as fatigue and noise. Blood pressure is another common measure that has been described as unreliable if used alone (Castor et al., 2003). Respiratory rates are used in occupational fields and fit more static/indoor cycling studies. Respiration is used to correct heart rate measures but does not qualify as a workload measure by itself (Wilson et al., 2004). Recently, a study demonstrated that the perception of safety can be measured proactively with traveler biometrics, including eye and head movements. The study concluded that high readings of biometric indicators correlate with less safe areas, which makes those measures valuable for future workload studies (Ryerson et al., 2021).

On the other hand, EDAs are good for sudden changes in workload levels, but they could be impacted by temperature and are sensitive to secondary tasks. Authors have argued that EDA appears to be the most dependable factor for inferring emotions, but quantitative validation of these findings is still needed. Physiological measures are beneficial because they do not interfere with the primary task, are easy to compare across studies, and do not require large sample sizes. The same study, which summarized 91 studies from various databases, identified that physiological measures had been used to understand pilots' (aviation), drivers' (motor vehicles), and operators' (nuclear power) workloads. Standard measures were cardiovascular, eye movement, EEG, respiration, skin sensitivity, EMG, and neuroendocrine measures accompanied by subjective workload. The results emphasized the criticality of choosing the correct measure for the application while cross-validation using different measures such as subjective, performance, or both measures. Table 2 goes over candidate workload measures that have been used in the literature and represent good candidates for cycling studies.

**Table 2. Comparison of Selected Workload Measures and their applicability in Cycling Environments**

| Test | Merits | Disadvantages | Recommendations |
| --- | --- | --- | --- |
| **Subjective workload measures** | 1 - Economically feasible<br>2 - Effortless<br>3 - Quick | 1 - Difficult to be done during the primary task (cycling)<br>2 - Prone to bias and perception<br>3 - Subjective measures cannot provide moment-to-moment assessment (Lal & Craig, 2001)<br>4 - Mistakes in understanding the questions or/and instructions | 1 - Complement by other workload measures to overcome subjectivity<br>2 - NASA TLX ratings should be collected within 15 mins after cycling sessions (Moroney et al., 1992). |
| **Heart rate variability** | 1 - A good measure for e-bikes<br>2 - Decrease in heart rate is an indicator of fatigue in car driving (Lal & Craig, 2001) | 1 - Prone to infrastructure: for example, terrain grades<br>2 - Different human capabilities mean different recovery levels for cyclists (Danieli et al., 2014) | 1 - Complement by other workload measures such as theta wave brain power and subjective measures<br>2 - Better if a significant and diverse sample size is used |
| **Vigilance**<br>(Reaction times or errors made) | 1 - Indicator of fatigue mainly due to sleep deprivation<br>2 - Possible indicator of boredom (E. Grandjean, 1979) | 1 - Impacted by age<br>2 - Impacted by environmental factors such as noise, vibration, and ambient temperature (Davies & Parasuraman, 1982) | 1 - Promising application for cyclists with sleep disorders (I. D. Brown, 1967)<br>2 - Different personalities, anxiety, and temperament impact results *(54)* |
| **Pupil diameter** | 1 - Measures variation in workload<br>2 - Good for laboratory experiments and on-site | 1 - Impacted by effort or fatigue and emotional states (Cain, 2007; Murata, 1997)<br>2 - Vary by luminosity (Beatty & Lucero-Wagoner, 2000; Qin et al., 2021) | 1 - Pupil data collection suffers distortion due to blinking and requires extensive data processing (Pomplun & Sunkara, 2003) |

| Test | Merits | Disadvantages | Recommendations |
|---|---|---|---|
| **EEG**<br>(Delta activity, Theta frequency, Alpha waves, and Beta waves) | 1 - Delta activity measure transition to drowsiness and sleep state<br><br>2 - Theta frequency is promising for measuring low levels of alertness (decreased information processing) and time pressure<br><br>3 - Alpha waves are indicator of alertness in relaxed state, memory load, and task difficulty.<br><br>4 - Beta waves express increased alertness, arousal and excitement (E. (Etienne) Grandjean, 1988; Lal & Craig, 2001) | 1 - EEG is impacted by individual abilities such as introversion and extroversion, sex and spatial abilities (Lal & Craig, 2001)<br><br>2 - Theta activity could be impacted by age<br><br>3 - Alpha waves are impacted by gender (Santamaria & Chiappa, 1987)<br><br>4 - No known application in commuting cycling but high-intensity cycling only (Irvine et al., 2022)<br><br>5 - EEG is sensitive to fluctuations in vigilance | 1 - Beta waves are promising in the area of reaction-time task (Sheer, 1988)<br><br>2 - Some suggest EEG measurement suffer higher drowsiness in simulator setting in car driving (Hallvig et al., 2013)<br><br>3 - EEG data processing is a promising area of research due to high noise levels from eye blinking, jaw clenching, muscle movement, etc (Hogervorst et al., 2014). |
| **Eye movement and blinks** | 1 - Easily quantifiable<br><br>2 - Describe transition from wakefulness to drowsiness | 1 - Influenced by factors not directly related to workload such as fatigue (Cain, 2007) | 1 - Promising for future research as indicator of fatigue and drowsiness |

Among the physiological measures, we specifically review two that have been previously utilized in cycling experiments.

### Electrocardiogram (ECG)

Monitoring the mental workload of cyclists is crucial for ensuring both performance optimization and safety. One of the psychological techniques used to measure mental workload (MW) is the ECG, which records the electrical signals in the heart. ECG is one of the most widely used techniques for measuring the workload in driving tasks (Tan et al., 2019). Likewise, in dynamic systems, such as transportation, where safety factors are critically important, ECG is considered very sensitive to the MW (H. Qu et al., 2021) and has been tested in various research (H. Qu et al., 2021; S. Qu et al., 2022; Tjolleng et al., 2017). During the state of high MW in an operator, the cardiac load also increases, which leads to changes in the period of the ECG signal as well as the shape of ECG signals (H. Qu et al., 2021). The Autonomous Nervous System (ANS), which is responsible for governing our capacity to react to various external stimuli, is affected by mental stress (Castaldo et al., 2015). Hence, interpreting ECG data to assess cognitive workload involves analyzing various parameters that reflect ANS. Besides, studies have demonstrated a strong correlation between ECG-derived metrics and cognitive performance, which is crucial for decision-making and reaction times in competitive or high-traffic cycling environments (Backs & Seljos, 1994).

Because of its practicality and non-invasive nature for field use, ECG is very suitable for monitoring cyclists continuously without affecting their natural movements. For evaluating the MW using ECG output, various methods such as time-domain, frequency-domain, and nonlinear analyses are used. The statistical measurements, including mean, root mean squared differences (RMSSD), and standard deviation (SDNN) of Inter beat intervals (IBIs), are performed in the Time Domain Method (Tjolleng et al., 2017). The frequency domain method measures the power in low and high frequencies (LF and HF) and the ratio of LF/HF (Tjolleng et al., 2017). Nonlinear analyses include the measure of Sample Entropy, Correlation Dimension, Detrended Fluctuation Analysis, and Approximate Entropy (Shaffer & Ginsberg, 2017). Each of the aforementioned methods provides a comprehensive understanding of cognitive stress and fatigue, with each method offering a distinctive view of how mental workload affects the heart rate (HR). Among the various other indicators, the ECG indicators, which measure a driver's HR and its variability (HRV) during a driving or tracking task, are the most widely used (Shakouri et al., 2018). HRV is an equilibrium indicator between the parasympathetic and sympathetic aspects of the autonomic nervous system. When the MW is high, HRV tends to decrease, whereas a low MW corresponds to an increase in HRV. ECG measures have been used in various ways in cycling to assess and manage MW, optimize performance, and ensure safety. Using the ECG, HRV was monitored among the cyclists during the recovery phase after exercise, and it was found that HRV measurements can be used as a recovery index (Salam et al., 2018). Likewise, the ECG was used to measure the HRV to detect the emotional states of electric bicycle riders to improve the safety of the cyclist as well as improve the riding experience (Dastageeri et al., 2019). Additionally, a field-based study utilized ECG to measure cyclists' workload, validating heart rate variability

(ΔHRV) levels against subjective survey measures (S. Qu et al., 2022). The CART algorithm classified workload thresholds: normal condition (ΔHRV ≤ 19), higher workload (19 < ΔHRV ≤ 79), and highest workload (ΔHRV > 79). In conclusion, ECG is a very effective method to assess the MW of cyclists. By monitoring the HR and HRV, we can ensure the safety of cyclists and integrate advanced technological solutions to support cyclists.

### Eye Tracking

Methods for evaluating stress and mental workload in drivers however are well studied, and often utilize eye tracking as one measure. Eye trackers are essential devices for monitoring where cyclists look, providing researchers with valuable data on their gazing behavior, glances, distractions, areas of interest (AOIs), gaze sequences, and durations. Additionally, eye tracking is a well-established method for evaluating stress and cognitive workload not only in drivers but across many fields, including fields unrelated to transportation (Ryerson et al., 2021). Eye tracking, however, is not a singular task. Eye movement consists of saccades – quick eye movements with short durations, smooth pursuits – movement in which the eyes smoothly follow a target, and fixations – little to no movements of the eyes and held for a brief moment, additionally fixations are separated by saccades. Each of these movements can be tracked with eye tracking technology (Ahlstrom et al., 2012; Gadsby et al., 2021; Mantuano et al., 2017; Pashkevich et al., 2022; Rupi & Krizek, 2019). Fixations are often the most studied and useful for understanding factors affecting cyclists. However, the researchers make use of an inbuilt gyroscope to measure head movement, gaze velocity – a measure similar to saccades, and off-mean gaze distance – a measure similar to fixation, and they found that the inclusion of head movement allowed for a better understanding of mental workload (Ryerson et al., 2021).

Along with eye tracking not being synonymous with eye movement, eye tracking is also not a singular technology. Generally there are two major types of eye tracking that are used in studies concerned with mental workload, those being either mobile or “head-mounted” eye tracking, which was used in (Gadsby et al., 2021; Mantuano et al., 2017; Pashkevich et al., 2022; Rupi & Krizek, 2019; Ryerson et al., 2021), and remote eye tracking, which was used in (Ahlstrom et al., 2012). Of the two types, mobile eye tracking, which is used in this project, is generally regarded as the more favorable of the two, especially in naturalistic studies, due to less data loss, higher accuracy, and a wider field of view relative to remote eye tracking. Mobile eye tracking, as mentioned above in (Ryerson et al., 2021), can also be combined with gyroscopes to measure head movement, which can provide an additional element of robustness to eye tracking studies. This also allows for a deeper understanding of factors affecting cyclists, such as the presence or absence of protections (Ryerson et al., 2021) or of the quality of the roadway (Gadsby et al., 2021).

Using eye tracking and galvanic skin response (GSR) in a simulator study, researchers examined the effect of loading zones on cycling (Jashami et al., 2024). Results showed the lowest GSR levels with commercial vehicles in maximum loading zones, while the presence of couriers increased stress. Eye tracking revealed that cyclists fixated on trucks, particularly on hand trucks, with the highest fixation time when couriers were moving. These findings are crucial for developing guidelines for loading zones near cycling lanes. Notably, two participants were excluded due to simulator sickness, highlighting the advantages of naturalistic studies for certain conditions, though simulators are valuable for studying hazardous scenarios.

### Naturalistic Studies

The choice of a naturalistic study is a pivotal contribution to research on cycling, offering significant advantages over controlled simulations. Naturalistic studies involve data collection in real-world circumstances, eschewing control over parameters such as temperature, wind, lighting, noise, drowsiness, and perceived safety—common limitations in simulated environments (Winter & Happee, 2012). Naturalistic studies are particularly valuable in identifying pre-crash causal and contributing factors (V. Neale et al., 2005). While such methodologies have proven successful in automotive research, their application to active transportation, such as cycling, presents unique challenges. Unlike vehicular environments, cycling involves diverse infrastructure, higher interactions with other road users, and varying exposure to environmental elements and speeds. Additionally, interpreting physiological data in cycling demands greater expertise due to the interplay between physical exertion and physiological responses (Dozza & Fernandez, 2014).

Designing a naturalistic study for cycling necessitates a deep understanding of both the natural environment and the limitations of the sensors employed. For example, electrodermal activity (EDA), sensitive to sudden workload changes, is unsuitable for cycling studies due to its susceptibility to ambient temperature variations (Qu et al., 2022). Electromyography (EMG), used to detect muscle strain and movement, has limited application in assessing stress, comfort, or workload levels without supplementary sensors and may interfere with cycling. In contrast, ECG is chosen for its superior ability to measure stress and workload, integrating both mental and physical aspects of the cycling experience (Hogervorst et al., 2014).

In summary, naturalistic cycling studies offer a robust framework for capturing authentic data, essential for understanding the complexities of cycling behavior and safety. The strategic selection of non-intrusive sensors and comprehensive study design enhances the reliability and applicability of the findings in real-world cycling contexts (Dozza & Werneke, 2014).

### Level of Service

Using naturalistic studies on bicyclists could help rethink methodologies for assessing Bicycle Levels of Stress (BLTS). The Bicycle Level of Service (BLOS) was developed based on extensive research, utilizing data from more than 250,000 miles of urban, suburban, and rural roads and streets across North America (Landis et al., 1997). The BLOS intends to measure bicycling suitability -or compatibility as recognized by FHWA- based on factors such as road and bike lane widths, vehicle speed and type, pavement conditions, parking, and traffic volumes (FHWA, 1999). One of the major benefits of BLOS is predicting route choice for cycling. There are many methodologies for BLOS depending on the author of the method, such as Bicycle Safety Index Rating, Florida Roadway Condition Index, Bicycle Interaction Hazard Score, Danish Bicycle LOS, and Evaluation of Bicycle Suitability, among others (Pritchard et al., 2019).

However, a significant drawback of the BLOS methodology is its reliance on factors such as average annual daily traffic (AADT), target speed, and the number of through lanes. While these metrics are feasible and simplified, they ignore many other factors that may impact cyclists' level of stress, such as pavement quality, cyclists' mood, physical state, different intersection designs, and the number of intersections per unit distance. To address these limitations, the use of biosensors has emerged as a valuable tool to quantify and micromodel traffic stress, offering a more comprehensive understanding than the current generalized BLOS.

Nowadays, many DOTs are using BLTS to design cycling and complete street infrastructure on state roads. Two notorious examples are Oregon DOT and Washington State DOT (ODOT, 2024; WSDOT, 2023). In the case of the Oregon Department of Transportation (DOT), BLTS is associated with various types of cycling facility users. These users are categorized into six design user profiles: highly confident, somewhat confident, interested but concerned, school-aged children, adult bicycle groups, and families. These profiles are detailed in Table 3.

**Table 3. Level of Traffic Stress and Design User Profiles Likelihood that User Profile will Ride (Table 900-3 ODOT Manual)**

| Level of Traffic Stress | Highly Confident Individual | Somewhat confident Individual | Interested but Concerned Individual | School-aged Individual Child | Adult Bicycle Group | Family Group |
|---|---|---|---|---|---|---|
| BLTS 1 | Likely | Likely | Likely | Likely | Likely | Likely |
| BLTS 2 | Likely | Likely | Sometimes | Sometimes | Likely | Sometimes |
| BLTS 3 | Likely | Sometimes | No | No | Likely | No |
| BLTS 4 | Likely | No | No | No | Sometimes | No |

BLTS profiles help planners understand the varying levels of comfort and stress experienced by different types of cyclists, enabling more targeted and effective infrastructure improvements. For example, a BLTS 1 route is suitable for all user profiles, ensuring a high level of comfort and safety, while a BLTS 4 route might only be appropriate for highly confident cyclists and not for more vulnerable groups like children or families.

To further enhance BLTS methodologies, incorporating naturalistic studies can provide deeper insights into cyclists' real-world experiences. These studies use biosensors and other advanced technologies to measure physiological responses to different cycling environments, capturing data on stress levels, heart rate, and other indicators. By integrating this data, planners can refine BLTS models to better reflect the nuanced factors affecting cyclists' stress, leading to more precise and effective infrastructure designs.

The literature on evaluating cycling safety and workload identifies three main types of studies: field-based, simulator, and naturalistic. Early research focused on validating human factors (HF) measures, but the scope has since expanded to develop practical applications. Historically, surveys were the primary tool for quantifying perceived safety, offering the advantage of quickly gathering data from large samples. While objective measures from biosensors provide precise data, surveys remain invaluable for capturing aspects that biosensors cannot efficiently measure. The integration of subjective and objective measures represents a significant advancement in the field.

Furthermore, while the BLOS has greatly enhanced our understanding of bicycling suitability, there is a growing need to evolve these methodologies. Leveraging naturalistic studies and advanced technologies can lead to more comprehensive and accurate assessments of BLOS, ultimately creating safer and more enjoyable cycling environments for diverse user profiles.

## Data and Methodology

The team designed and conducted data collection. The different devices and specific setups of the data collected are described in the following sections. Additionally, particular data cleaning methods, analysis, and processes are explained here. As part of this project, we also conducted a comparative study between different users. Figure 1 presents an overview of the project execution.

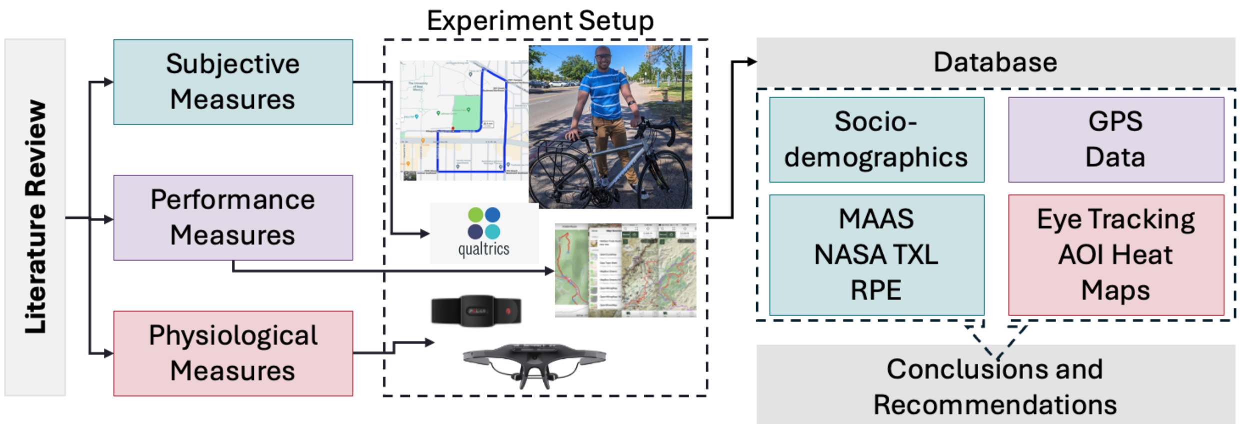


**Figure 1. Overview Project Execution**

### Experiment Design

The data collection process was designed to gather accurate and representative subjective, physiological, and performance data in a naturalistic setting, thus avoiding the inaccuracies often associated with simulator environments. The data collection described in this study required approval from the Institutional Review Board (IRB), which was obtained from the University of New Mexico under Protocol Number 2403118510. The collected data included surveys, electrocardiogram (ECG) readings, eye tracking data, and speed profiles. Details about the data and devices used for each specific measure are provided in the following sections. However, a summary of the collected data is presented in Table 4.

**Table 4. Summary of Data Collected**

| Data Type | Category | Data collected |
|---|---|---|
| Pre-experiment Survey | Subjective Measure | Age<br>Gender<br>Transportation Habits<br>History of Crashes |
| Post-experiment Survey | | NASA TLX |
| Speed Profiles | Performance Measure | GPS Data |
| ECG | Physiological Measure | RMP |
| Eye Tracking data | | Gaze Behavior |

One of the major contributions of this project is the choice of a naturalistic study. ECG was chosen as a superior measure of stress and workload because it provides a more direct and non-intrusive assessment of physiological responses to these conditions. As part of the experiment, the research team also recorded the time and day of the experiment, the temperature, and the wind speed. This information would be used to make further inferences.

### Subjective Measures

Subjective measures about respondents were collected before and after the ride during the experiment (Appendixes A and B). We used Qualtrics and a mobile device (table or cellphone) to request the information.

The introductory questionnaire began with a consent signature for participation in this study. Then, sociodemographic characteristics such as age, gender, educational attainment, race, and household composition were questioned. The questionnaire also asked the subjects if they had a driver's license and had ever been in an accident while driving a car or riding a bike.

The following section inquired about travel habits and micromobility usage to assess the frequency and purpose of trips. Additionally, we included questions about their decision to ride a bike and their personality traits, which are summarized in Table 5, along with the corresponding sources.

**Table 5. Pre-Survey Questions from Previous Studies**

| Section | Question | Source |
|---|---|---|
| Travel Habits and Micromobility | Do they consider the time of day when you cycle or use an e-scooter? | (Engbers et al., 2018) |
| Travel Habits and Micromobility | Do you consider the weather when deciding when to cycle or use an e-scooter? | (Engbers et al., 2018) |
| Personality Statements | How satisfied are you with your health? | (Engbers et al., 2018) |
| Travel Habits and Micromobility | How likely are you to listen to music with headphones while riding a bike or e-scooter? | (de Waard et al., 2010) |
| Travel Habits and Micromobility | How likely are you to listen to music with a speaker while riding a bike or e-scooter? | (de Waard et al., 2010) |
| Travel Habits and Micromobility | How likely are you to talk to other cyclists, passengers, pedestrians on your route? | (de Waard et al., 2010) |
| Personality Statements | How likely is it that you would ride micromobility devices in the eight different infrastructure. | (Bernhoft & Carstensen, 2008) |
| Personality Statements | Six statements from MAAS | (Brown & Ryan, 2003; Young et al., 2020) |

For the post-ride survey, the questions were primarily based on the NASA TLX (Hart & Staveland, 1988; S. Qu et al., 2022) and the Borg RPE scale (Borg, 1982), with additional input from secondary sources such as Nazemi et al. (2018). These questions aim to evaluate task performance, improve system design, and understand user experience by identifying areas where workload can be reduced. Given that the subjective measures were sourced from previous literature, particularly those related to infrastructure usage, MAAS, NASA TLX, and the Borg RPE scale, we also assessed their internal consistency using Cronbach's alpha. Cronbach's alpha values range from 0 to 1, with higher values indicating greater internal consistency. The interpretation of Cronbach's alpha can vary by field, but the generally accepted thresholds are: $\alpha \geq 0.9$: Excellent internal consistency, $0.8 \leq \alpha < 0.9$: Good, $0.7 \leq \alpha < 0.8$: Acceptable, $0.6 \leq \alpha < 0.7$: Questionable $0.5 \leq \alpha < 0.6$: Poor, $\alpha < 0.5$: Unacceptable.

### Performance Measures

The Gaia GPS app was used for our GPS tracking, which we had installed on the project mobile device (Gaia GPS, 2024). Each subject had to carry a mobile device during the cycling experiment, and the app tracked the GPS coordinates of each subject during the whole session. The app records the paths and offers distance, elevation, and speed data. Furthermore, the app provides a visual representation of the tract covered by each subject and a graph, enhancing our ability to analyze and interpret the data effectively. The app recorded each survey session's start and end times, along with the subjects' moving speeds and any periods when they stopped. The coordinate data of each subject was recorded on the Gaia app. The recorded GPS coordinates on the Gaia app were later extracted to analyze the data.

### Physiological Workload Measures

Two physiological measures were collected as part of the experiment: ECG and Eye Tracking Data. For the ECG, Polar Verity was used to measure the heart rate of each subject. The device measures the heart rate with maximum precision while engaging in high-intensity exercise (Polar US, 2024). Furthermore, the device was connected to the experiment mobile device through Bluetooth and ANT, allowing for the real-time monitoring of heart rate data in the field. During the survey, the subjects were made to wear the device on their forearm, which was connected to a mobile device that each subject had to carry during their cycling session. Because of its portable size of 65 mm ×34 mm ×10 mm and weight of 60 grams, it did not create any obstacles during the riding session for each subject. ECG data of each subject was recorded on the Polar app on the mobile phone. The recorded ECG data was later extracted from the Polar app to analyze the data. The Polar app also provided a graphical representation of the heart rate in BPM throughout each session, offering insights into the subjects' heart conditions during their rides.

The second device considered to capture physiological workload measures was the eye tracker. The eye tracker used in the experiment is the Neon by Pupil Labs. The eye tracker makes use of multiple cameras: one camera per eye and a forward-facing scene camera. The eye tracker also contains an accelerator, magnetometer, gyroscope, and dual microphones. Additionally, the tracker can hold up to 25 hours of storage, and the onboard battery can support up to four hours of recording. The data processing included eye fixation, our primary focus, along with additional factors such as blink data. The data collected were uploaded to the Pupil Labs cloud for further processing. Using Pupil Labs software, the data were analyzed to ensure accurate and comprehensive results. This approach highlights the role of Pupil Labs devices and services in both data collection and processing, which strengthens the reliability and precision of the measurements. The eye tracker's frame weighs 30 grams and is constructed from PA12 nylon and CNC-machined anodized aluminum. This lightweight design minimizes any impact on the cyclists, ensuring naturalistic behavior during the experiment. The lens material is reflective, dust-resistant, and water-repellent, as shown in Figure 2.

A recent study evaluated the accuracy of the Neon eye tracker in assessing gaze-estimation precision (Baumann & Dierkes, 2023). The findings demonstrated that the eye trackers function robustly across various lighting conditions, from total darkness to bright sunlight, and accommodate different eye appearances and head positions. Detailed results of this validation are available in the "Neon Accuracy Test Report" by Baumann & Dierkes, (2023).

**Figure 2. Neon's Eye Tracker**

For equity considerations, Neonnet was trained using a diverse dataset that included a wide range of eye and skin colors, as well as variations introduced by contact lenses. Additionally, the training data encompassed different facial geometries and eye makeup, ensuring an inclusive data collection process. The frame used in the Neon eye tracker is lightweight and adjustable, providing a comfortable experience for users with varying head sizes. Furthermore, the Neon eye tracker is compatible with or without helmets, ensuring maximum safety for bicycle riders.

### Route Description

The route was roughly 1.4 miles, starting and ending at the Lobo Bike Shop (Yellow pin on Figure 3) on the UNM campus. The main intersections on the route (listed in clockwise order) are Redondo Dr. NE & Campus Blvd NE, Girard Blvd NE & Campus Blvd NE, (Girard Blvd NE/SE, Monte Vista Blvd NE, & Central Ave SE/NE, #1 in figure), Girard Blvd SE & Silver Ave SE (#2 in figure), Stanford Dr. SE & Silver Ave SE, (Stanford Dr. SE/NE & Central Ave SE/NE), and Stanford Dr. NE and Redondo Dr. NE. A map of the route is presented in Figure 3.

The route encompasses five distinct bike infrastructure types. Beginning from the starting point and extending to the Girard Blvd NE & Campus Blvd NE intersection, this segment is designated as a bike route according to the Albuquerque Bike Plan. However, it lacks specific infrastructure tailored for cyclists. Transitioning into Girard Blvd SE, the landscape changes with three distinct types of cycling infrastructure. Sections marked in yellow boast buffered lanes featuring a 1.8-foot buffer and a width of approximately 3.6 feet. In blue, designated bike lanes span about 3.7 feet wide, delineated by a mix of bolded and dashed lines for separation from vehicular traffic of 0.5 feet. Meanwhile, areas highlighted in light green solely feature Shared Lane Markings (SLMs), also known as “sharrows.” Silver Ave, depicted in purple, embodies the concept of a bicycle boulevard. These streets are designed to prioritize bicycle travel, characterized by low motorized traffic volumes and reduced speeds—capped at 18 miles per hour in this case study. Signage and pavement markings further augment safety measures and minimize interference from motor vehicles. Conversely, Stanford Dr. NE presently lacks specialized cyclist infrastructure. Nonetheless, it is a proposed bike route in the upcoming Albuquerque bike plan.

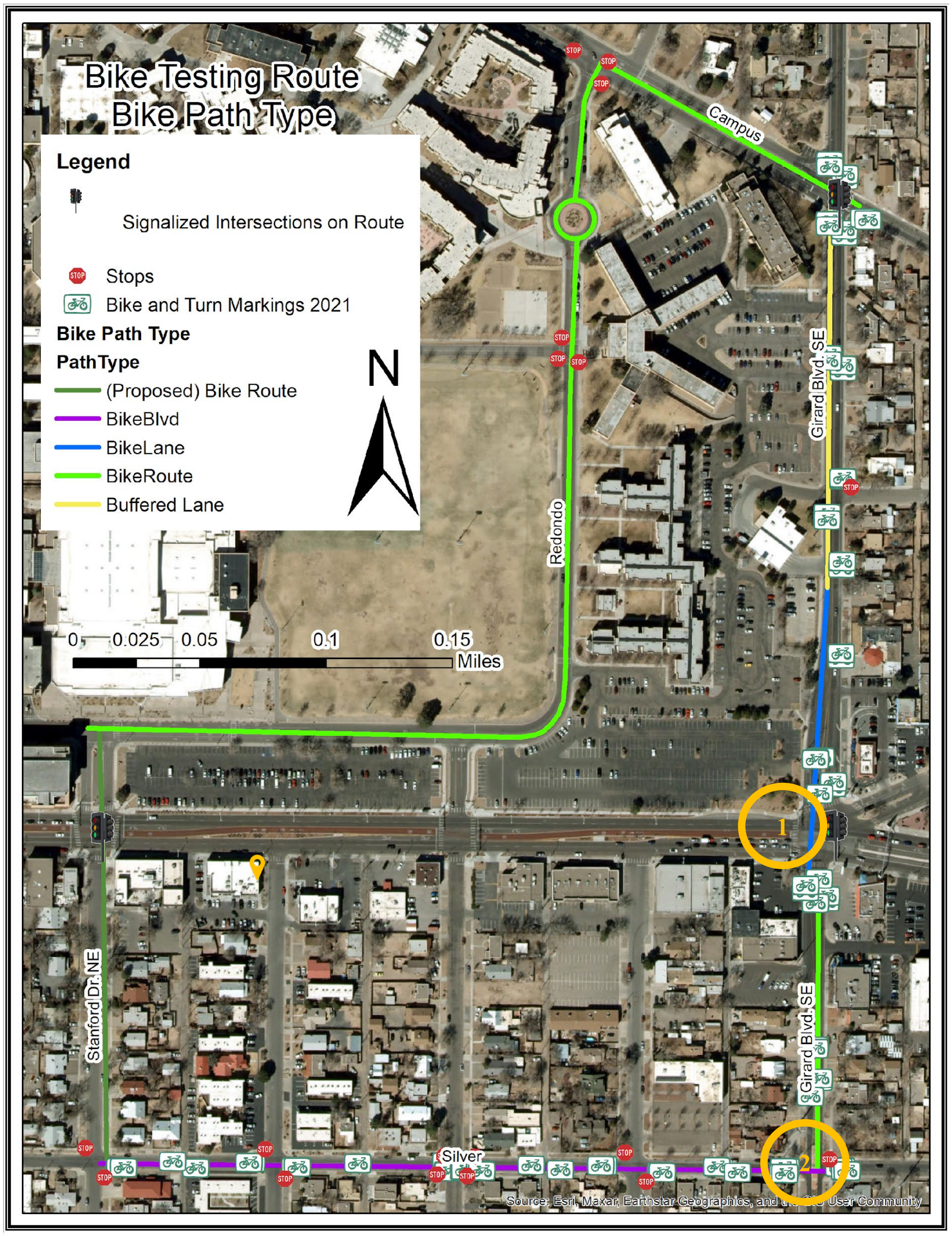


**Figure 3. Infrastructure type and signals along the route**

Along the route, there is also a variety of unsignalized and signalized intersections. Intersections are where we expect to observe higher stress levels in the cyclists, and the focus of this report. Notably, in the clockwise direction, there is a large elevation gain going from Girard Blvd NE & Campus Blvd NE to Girard Blvd NE/SE, Monte Vista Blvd NE, & Central Ave SE/NE, so we may observe an increased heart rate from this alone or in addition to stress. Across the route, there is an increase in elevation of 39' and a decrease in elevation of 39', with a net zero change in elevation. Figure 4 shows the current bicycle levels of traffic stress for the route as per City of Albuquerque guidelines. Most of the routes have nonexistent levels, while Girard and Silver are estimated to be at BLTS 1. Level of Stress 1 is often comfortable for all types of cyclists (Mekuria et al., 2012).

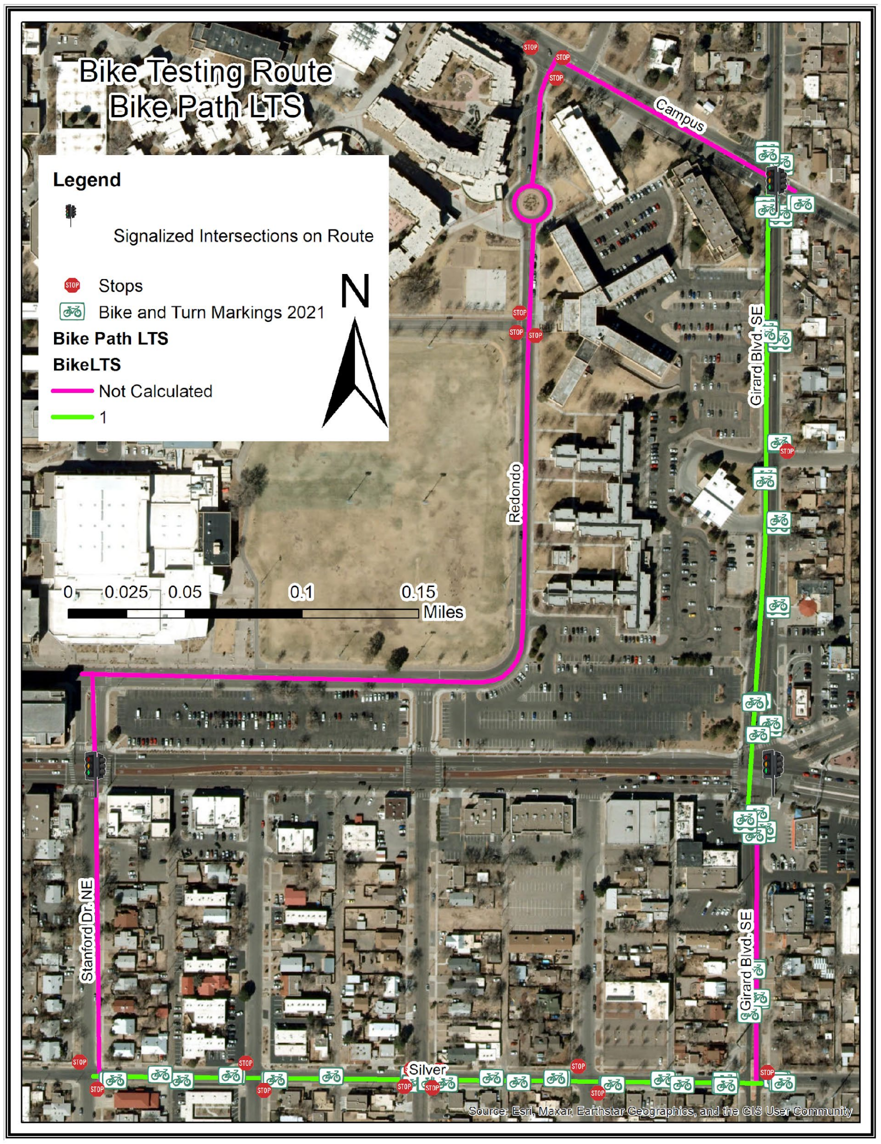


**Figure 4. Bicyclist Level of Streets on Route**

Finally, Figure 5 shows the roadway levels of traffic stress for the route's vehicular infrastructure. The map shows three different levels of traffic stress (LTS). Around Redondo, Girard, Silver, and Sandford, the segments are classified as LTS 1, Campus is classified as LTS 2, while Girard Blv.

between Central and Silver is classified as LTS 4. In this case, LTS refers to the level of stress considering all users of the road, not only cyclists. An LTS of 1 represents, again, a comfortable street to ride. Many residential streets are also classified as LTS 1 because they have low traffic volumes and slower vehicle speeds. An LTS of 2 serves most people who are interested but concerned. Despite the presence of bike lanes and signage, LTS 4 remains a high-stress bikeway due to its high traffic volume, posted speed limit, and lack of separation between motorists and cyclists. This route primarily appeals to only the most confident bicyclists.

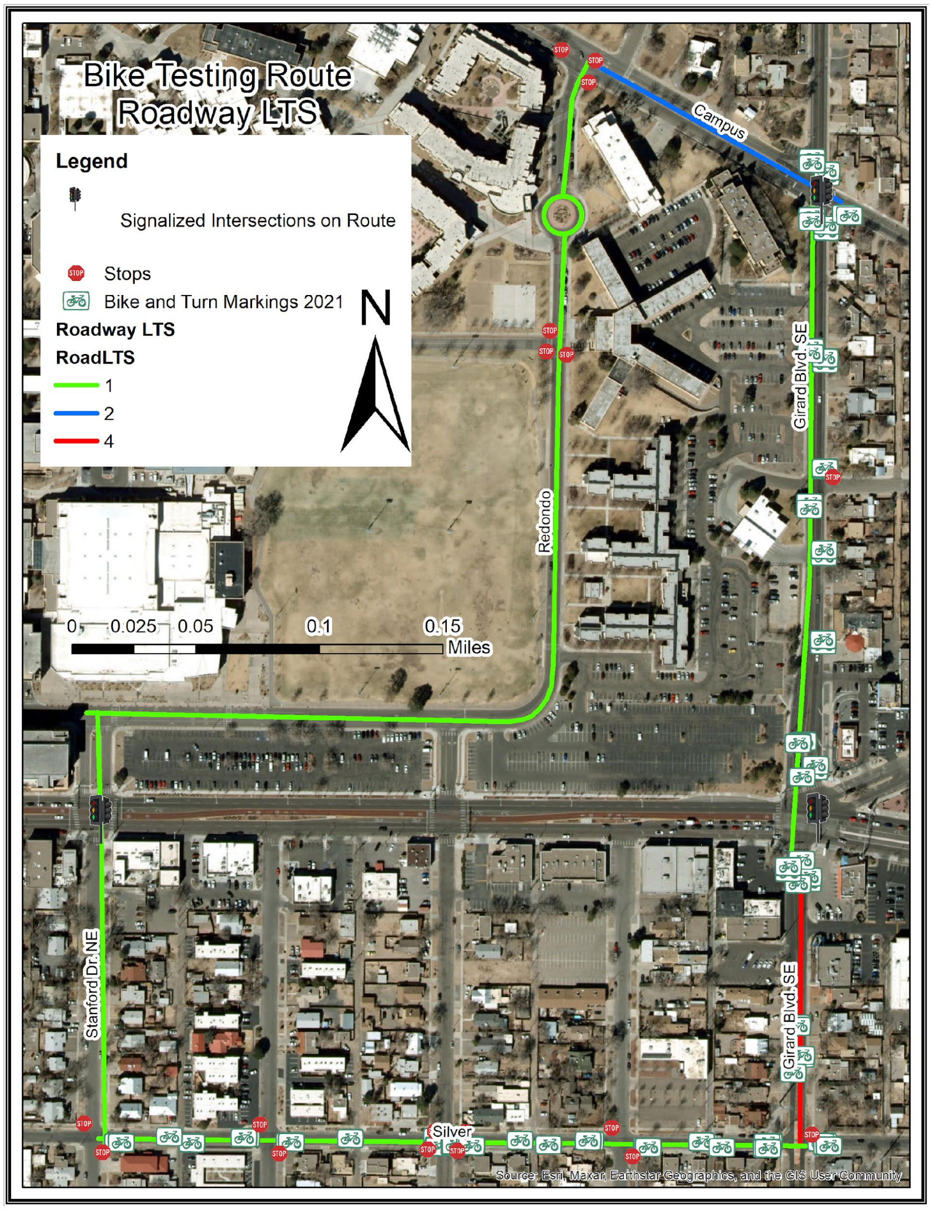


**Figure 5. Roadway Level of Streets on Route**

## Data Collection

The data collection consisted of participants who were adults older than 18 years old and had bicycle experience. Our sample ranged between 19 to 40 years old and an average of 31.6 years old. We recruited participants regardless of self-identified sex, resulting in 14 males, four females, and two non-binary individuals. All our subjects have a U.S. driver's license. Data collection occurred in May 2024, with temperatures ranging from 57°F to 88°F and an average of 72.6°F. Wind speeds varied from 3 to 23 mph, averaging 12.52 mph. The experiment was conducted in three consistent phases, as described below.

### Phase 1. Initial Phase

The initial phase consisted of three sub-steps. First, a tablet was used to obtain participants' consent and to administer the pre-ride survey, which included subjective questions. Those questions were discussed in the previous section and are attached in Appendix A. Additionally, the participants wore the different devices used as part of this study that aim to capture the heart's electrical activity using an electrocardiogram, gaze movement utilizing the eye tracking device described before, and a helmet. Once the participant had the equipment on, we collected one-minute heart rate measurements and calibrated the eye tracker to account for each participant's specific eye movements. The participants were also offered to wear a vest and a helmet. The data collected from the wearable biosensors was stored in the device and later downloaded to a computer as a .csv file to further process. To de-identify that procedure, each participant was given an ID that served to connect the different information.

Additionally, the researchers collected other important data to consider in the analysis, such as the time of the start of the first ride, the temperature (in Fahrenheit), and the wind and gust speed at the start time. This part lasted approximately 15 minutes.

### Phase 2. Bike Ride

The participant used the devices presented in the previous section, such as a heart rate sensor on the wrist and an eye tracker. Additionally, participants were given a belt bag to store the phone connected to the devices and GPS. The cyclists were shown a map of the route described in the previous section and were randomly assigned to start their ride in either direction. Participants were expected to take roughly 10 minutes to complete the route in either direction. However, they were instructed to ride at their own pace, cycling as they would on a normal day. All participants, except one, completed the route a second time in the opposite direction. This approach served to (i) double the amount of collected data, (ii) normalize route direction, and (iii) provide more individual cyclist information. Additionally, it was hypothesized that as cyclists become more familiar with a route, they may experience less stress, similar to a regular commute. Completing the route twice offered a simplified simulation of this effect. It is important to mention that participants were also allowed to take a five-minute break between both rides. This part of the experiment lasted about 30 minutes.

### Phase 3. Final Questionnaire

Once the two rides were completed, the participants returned the sensors to the researcher and completed the post-ride survey, which asked about their reactions to the experiment and can be found in Appendix B. Participants received a $20 Amazon gift card as compensation. The gift card was handed to the participant after completing the experiment, and no signature was required since they had already signed a consent form. If participants withdrew during part 2 of this 3-part study, they were compensated based on their participation in parts 1 and 2. For example, a $5 Amazon gift card was given to those who completed the consent form, and a $15 gift card was given to those who completed the ride but did not finish the remainder of the study. This compensation was deemed appropriate as it exceeded the minimum hourly wage in Albuquerque, which is $12 per hour. This phase of the experiment was expected to last about 5 minutes.

## Exploratory Data Analysis

Subjective, performance, and physiological measures were meticulously cleaned and processed to demonstrate their capabilities and derive insights for this report.

For subjective measures, we provide descriptive statistics, and comparative analyses using variables collected from questionnaires and ride-related information. The data, initially recorded in Qualtrics, was exported to Excel for cleaning and preliminary analysis. Pivot tables were utilized to interpret responses and generate graphs. Subsequently, the data was analyzed in Stata 16 to identify correlations and conduct further analyses. Given that subjective measures were collected both before and after the experiment, we also discuss their applicability in naturalistic experiments. Two analyses were conducted regarding performance and physiological measures. The team combined ECG data, often associated with stress, with GPS data to identify areas where participants experience higher stress levels. For this report, we will examine both ECG and GPS data from two specific intersections along the route, each with distinct characteristics. The first intersection is at Central Avenue and Gerard Avenue, and the second is at Silver Boulevard and Gerard Avenue. These intersections were selected for their different features.

The first intersection is a complex five-way intersection with traffic lights featuring a mix of protected bike lanes and buffered lanes. The second intersection has a median with a rest area for cyclists, making it easier to navigate. For the analysis, we separated the data collected 30 seconds before and after each intersection. We also included the heart rate and speed profiles of the subjects as they crossed the intersections. Various graphs were created to showcase the subjects' actions at the intersections. Additionally, we compared the first and second rides to determine if the second ride was less stressful. These analyses were performed using Excel.

Eye tracker data was processed using the Pupil Labs' Pupil Cloud web-based tool. The Pupil Cloud initially stored the participants' recordings, which could later be downloaded in .csv or other file formats. Additionally, the Pupil Cloud tool facilitated creating AOI heatmaps to visualize gaze patterns on AOIs with metrics such as dwell time, time to first fixation, and average fixation duration.

For this analysis, we focused on the two intersections described earlier to create a visual representation of the objects the subjects were considering while at the intersections (#1 and 2 in Figure 3). We expected subjects to fixate on signs, signals, and other vehicles or pedestrians they encountered before, during, and after crossing the intersections.

Creating the AOI heatmaps involved two main processes. First, the team recorded videos of the intersections and took pictures to create a Reference Image Mapper or Marker Mapper enrichment. Then, AOIs were delineated on the reference images or surfaces. These two steps enabled the creation of the heatmaps.

# Results

## Subjective Measures

Subjective measures were captured using pre- and post-ride questionnaires. From our sample, we observed that 70% of the volunteers were male, mirroring the percentage of male cyclists in the U.S. The average age of the male subjects was 33 years, while the average age of non-male subjects was 27.7 years, which also aligns with national cycling trends in the U.S. (Velotric, 2023). This also applies to the statistics on commuter bikers in Albuquerque (Table 6). Using a test of proportion, we compared our sample with the commuter bike population in Albuquerque using the 2022 American Community Survey's (ACS) 5-year estimate. According to the test, there is no significant statistical difference between our sample and the population in terms of gender. Our sample included three gender categories: female, male, and non-binary/third gender, the latter of which is not represented in the ACS data. When we combined the non-binary and female categories, our sample still showed no significant statistical difference from the general population.

Regarding age, our sample did not show a significant statistical difference for individuals younger than 24 years old. However, there was a significant difference between those aged 25 and those who were older. The majority of participants in our sample were between 25 and 44 years old, whereas this age group only represents 44% of bike commuters in Albuquerque.

**Table 6. Comparison between sample and bike commuters in Albuquerque**

| Characteristics | Study Sample (n=23) | | ACS 5-year estimate 2022 (n=2081, 0.8%) | | p-value | |
|---|---|---|---|---|---|---|
| Male | 70% | 16 | 68% | 1418 | 0.84 | |
| Non-Male | 30% | 7 | 32% | 663 | 0.84 | |
| 16 to 19 years | 4% | 1 | 3% | 57 | 0.78 | |
| 20 to 24 years | 9% | 2 | 9% | 180 | 1.00 | |
| 25 to 44 years | 87% | 20 | 44% | 912 | < .00001 | *** |
| 45 years and over | 0% | 0 | 45% | 932 | < .00001 | *** |

Upon further examination, our sample is highly educated, with 60% holding a bachelor's degree or higher. This may be attributed to our recruitment efforts, which were primarily conducted on a university campus and within work commuter groups. Additionally, 56% of our sample identified as Hispanic or Latino. Overall, 13% identified as Asian, 52% as Caucasian or White, and 34.74% as Other. On average, participants lived in households with 2.1 inhabitants. In terms of crashes, subjects in our sample reported fewer bike crashes compared to car crashes over the past three years, with seven reporting car crashes and only four reporting bike crashes.

The subjects who participated in the experiment primarily commuted by bike to work or school (Figure 6). However, for grocery shopping, personal errands, and social recreation, they preferred to use a car.

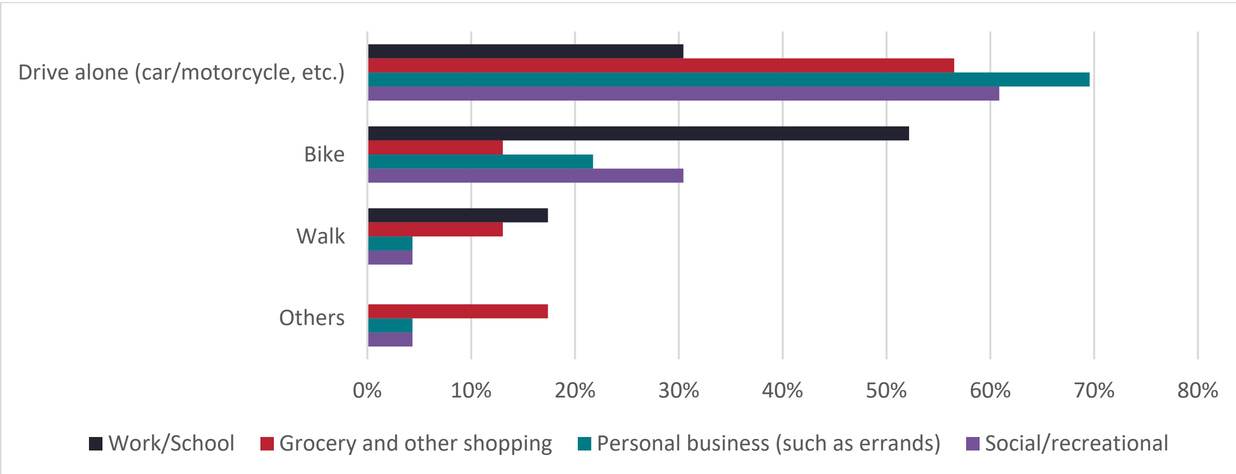


**Figure 6. Primary mode of travel for each trip purpose**

In our sample, individuals most frequently traveled for work or school. Additionally, social and recreational trips were more common than trips for personal errands or grocery shopping (Figure 7).

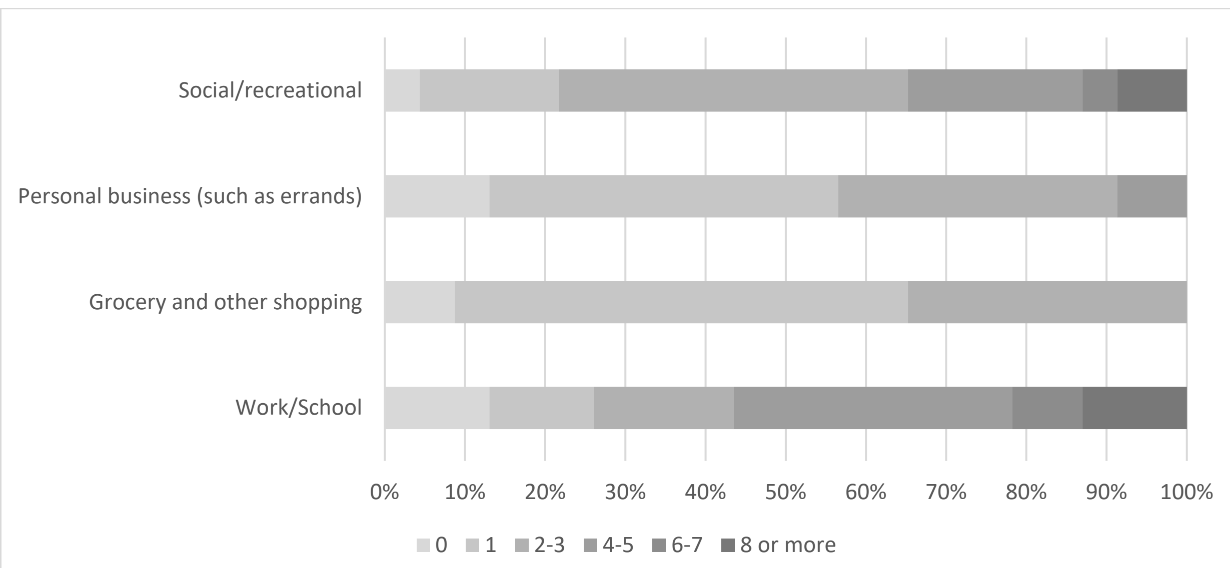


**Figure 7. Trip frequency for each trip purpose**

Figure 8 presents the likelihood of subjects using various types of infrastructure while biking (or using micromobility devices). Overall, subjects were highly likely to use routes with cycle paths or marked lanes at crossings. They also expressed a moderate to high likelihood of riding where there is good street lighting, smooth surfaces on cycle paths, minimal traffic, and signalized crossings. A notable percentage of subjects indicated they were extremely unlikely to use the fastest route.

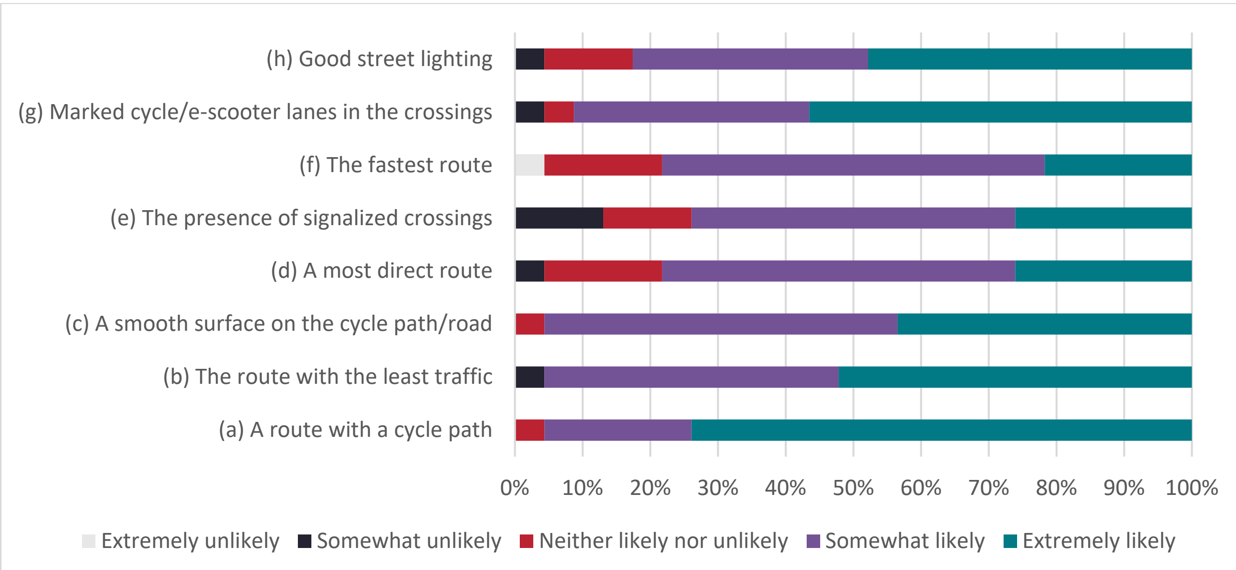


**Figure 8. Likelihood of riding on different types of infrastructure**

Further exploring differences between male and non-male participants in our sample, we found no major differences between males and non-males when comparing the means in most questions related to infrastructure (Figure 9). Despite the small sample size, we conducted t-tests and confirmed no significant differences between these two groups when analyzing certain statements. Non-males showed a higher preference for riding on smooth surfaces compared to males ($p = 0.0782$ at a 90% confidence level). Additionally, non-males were more likely to prefer the most direct route compared to males ($p = 0.0884$ at a 90% confidence level).

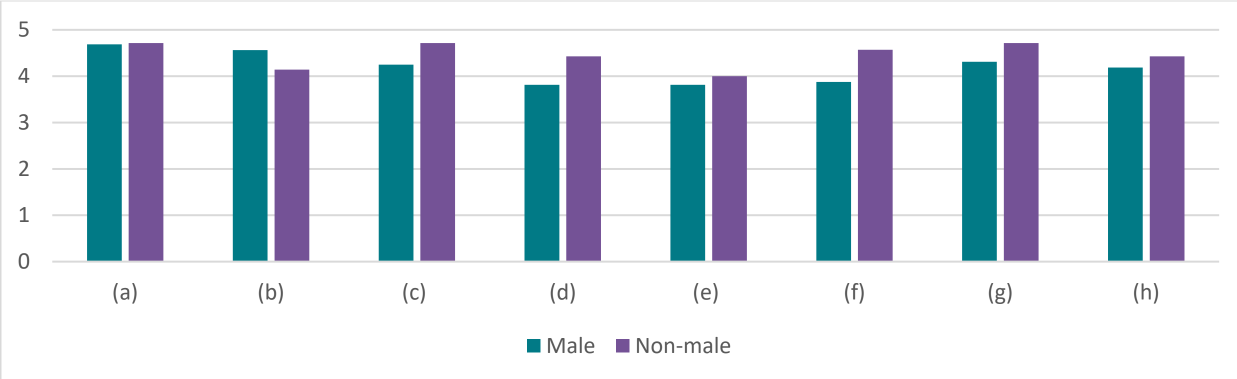


**Figure 9. Differences between male and non-male in infrastructure preferences**

The MAAS was evaluated in the pre-ride survey. Figure 10 presents the overall results from our sample. The statement with the highest level of agreement was, "I find myself listening to someone with one ear, doing something else," indicating a certain level of distraction among participants. Conversely, participants disagreed with the statements that they perform tasks without paying attention and that they drive to places on automatic pilot.

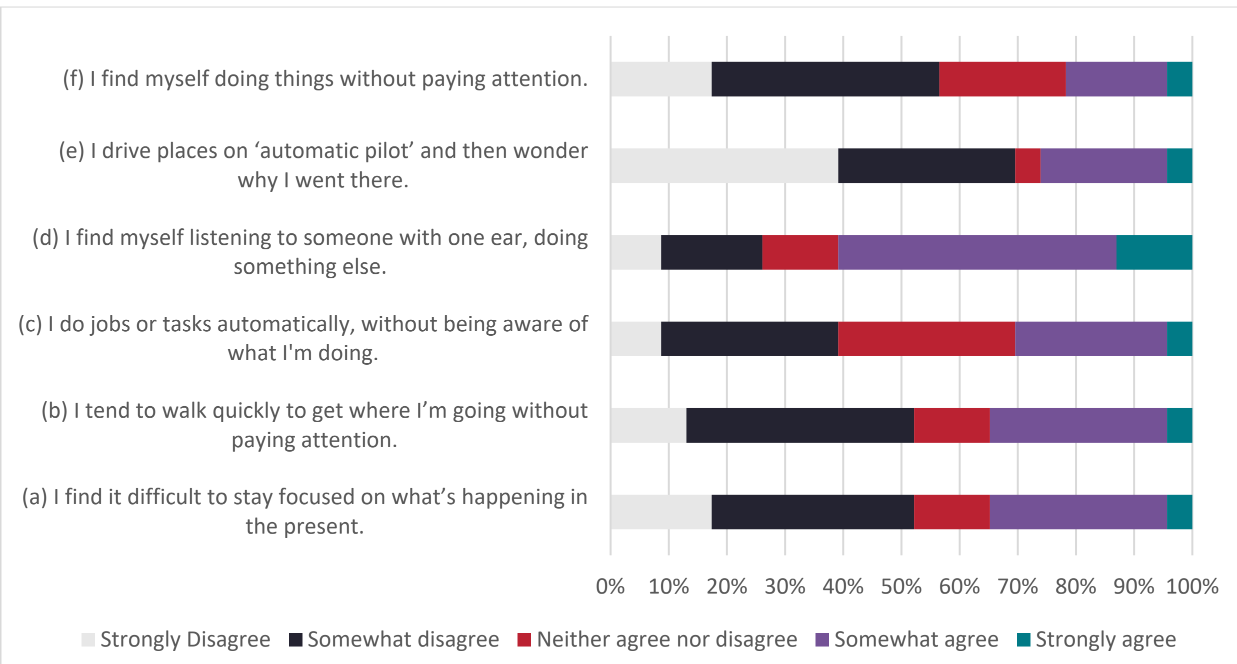


**Figure 10. MAAS General Results**

An analysis of gender differences in MAAS statements did not reveal any significant differences (see Figure 11Figure 15).

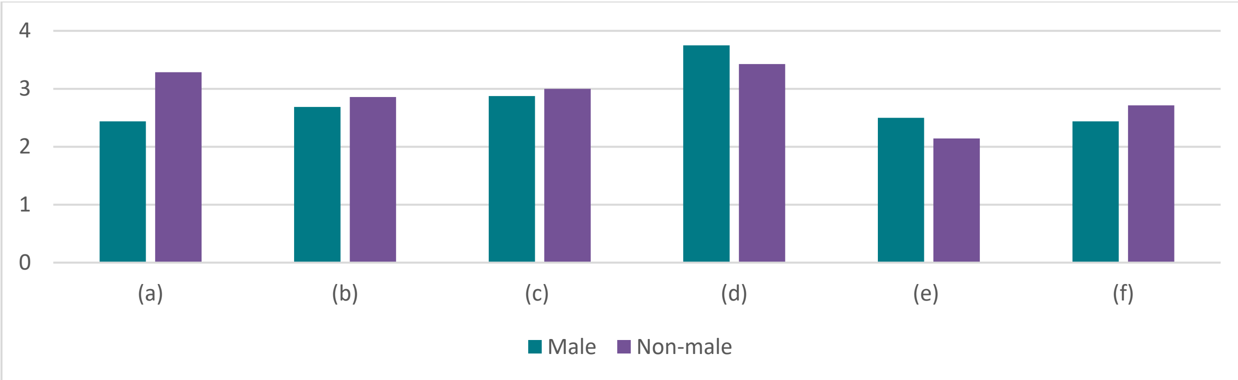


**Figure 11. Differences between male and non-male in MAAS**

The NASA Task Load Index (TLX) was evaluated using the post-ride questionnaire. This set of questions typically includes at least nine levels of ranking, with various statements assessing different outcomes (Appendix B). For all statements, a rank of 1 indicates the minimum agreement, while a rank of 8 indicates the maximum (Figure 12).

Our findings indicated that participants were less likely to report feeling insecure, discouraged, or irritated during the task. Additionally, participants did not feel that they had to exert significant effort to achieve their performance level. The majority of participants believed they were highly successful in accomplishing the task assigned by the research team. Overall, respondents ranked the task as more mentally demanding than physically demanding.

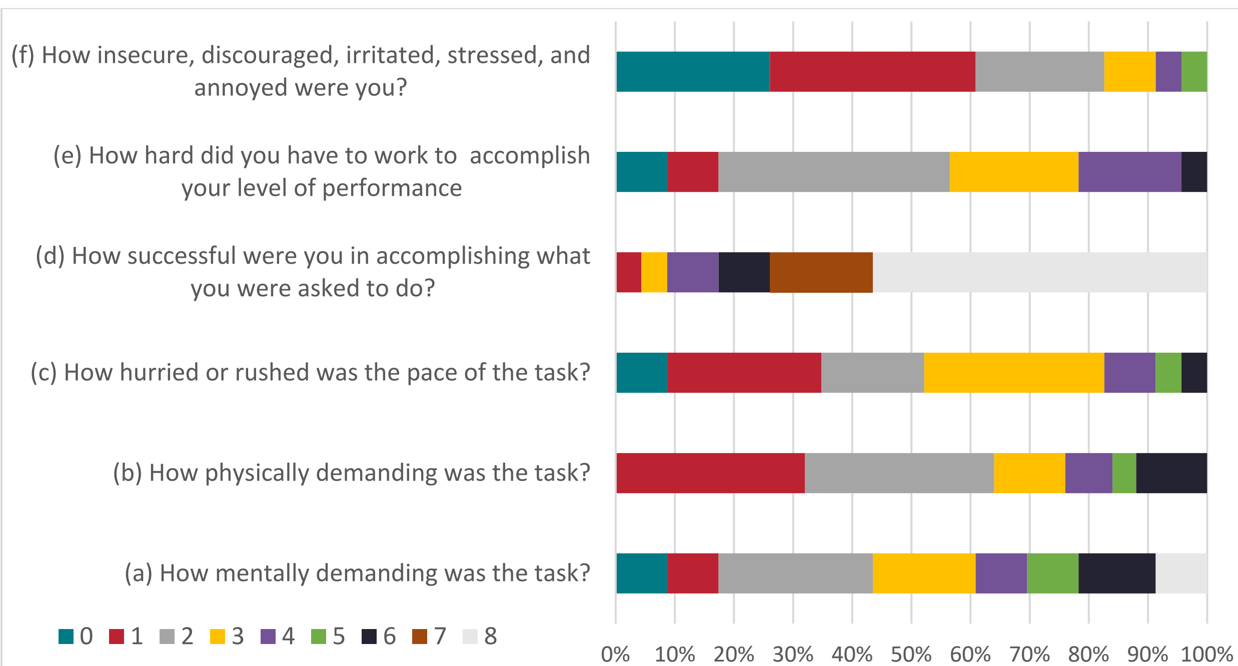


**Figure 12. NASA TLX Responses**

In the NASA TLX survey, gender differences were observed in responses to two specific statements (Figure 13). First, regarding the statement “How hurried or rushed was the pace of the task?”, non-male participants reported feeling less hurried compared to male participants, with a p-value of 0.0536 at the 90% confidence level. Second, in response to the statement “How insecure, discouraged, irritated, stressed, and annoyed were you?”, non-male participants reported significantly lower levels of these feelings, with a p-value of 0.0381 at the 95% confidence level.

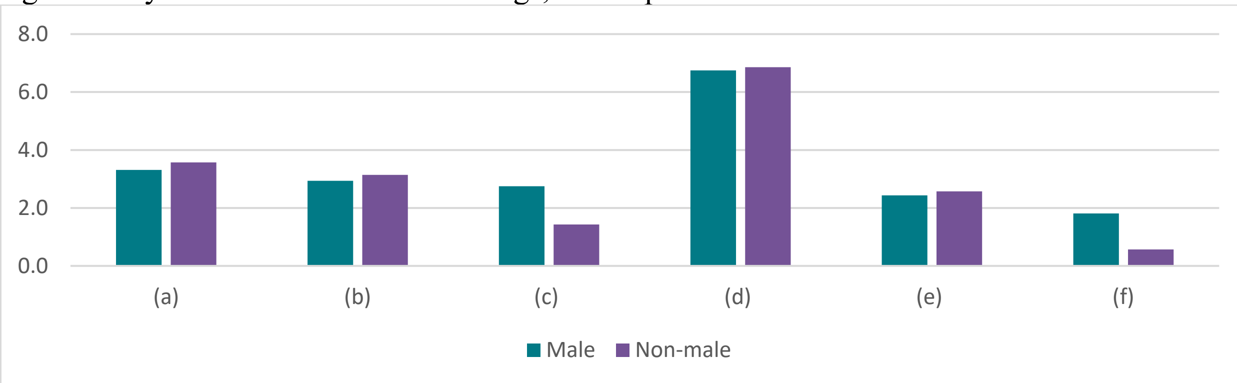


**Figure 13. Differences between male and non-male in NASA TLX**

The Borg RPE scale was incorporated into the post-ride questionnaire to assess participants' perceptions of physical workload. Four questions from the original Borg scale were included to capture these perceptions (see Figure 14). Overall, participants reported experiencing rapid or very rapid breathing and a fast heart rate. However, they did not report significant fatigue or excessive sweating.

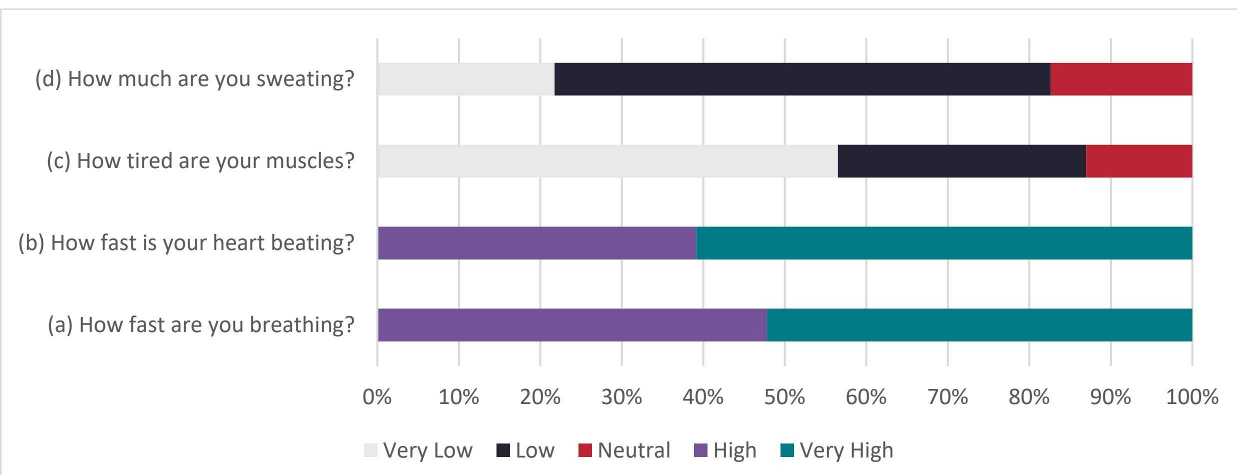


**Figure 14. Borg RPE General Responses**

An analysis of gender differences revealed no significant differences in responses to the RPE Scale questions (see Figure 15).

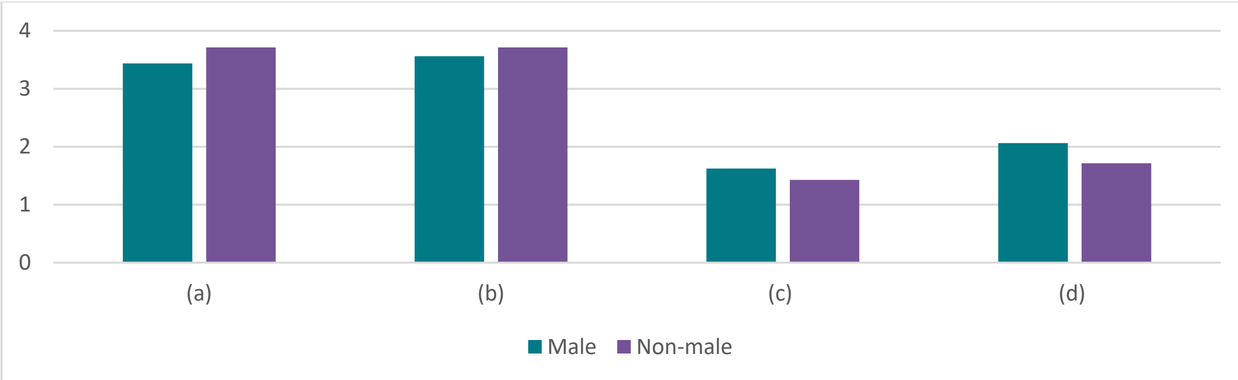


**Figure 15. Differences between Male and Non-male in Borg RPE Scale**

Finally, the internal consistency of the scales was assessed using Cronbach's alpha. The sample size for this analysis was 23 participants. The scales, consisting of 4 to 8 items, yielded a Cronbach's alphas between 0.72 and 0.78, indicating acceptable internal consistency. This suggests that the items measure the same underlying constructs reliably. The only exception was the NASA TLX construct, which yielded poor internal consistency.

**Table 7. Internal Reliability**

| Scale | Number of Items | Cronbach's alpha |
|---|---|---|
| Infrastructure | 8 | 0.72 |
| MAAS | 6 | 0.78 |
| NASA TLX | 6 | 0.57 |
| Borg Rate of Perceived Exertion | 4 | 0.73 |

### Subjective, Physiological, and Performance Measures

This section explores the use of subjective, physiological, and performance measures to study stress levels at intersections. Figure 16 shows the mean BPM at every intersection based on the respondents' stress levels from NASA TLX, covering both directions (1st direction and 2nd direction). The X-axis represents the stress level, which is classified into four categories: 0, 1-2, 3-4, and greater than 4, and the Y-axis represents the mean BPM ranging from 0 to 170 BPM. Histogram bars represent the mean BPM at every intersection for various reported stress levels among all subjects (subjective and physiological measures). The straight horizontal line represents the overall mean BPM of riding sessions for all subjects, covering both directions. We observed that even when reporting greater stress levels, the mean BPM was similar for all riders, with no direct lineal relationship.

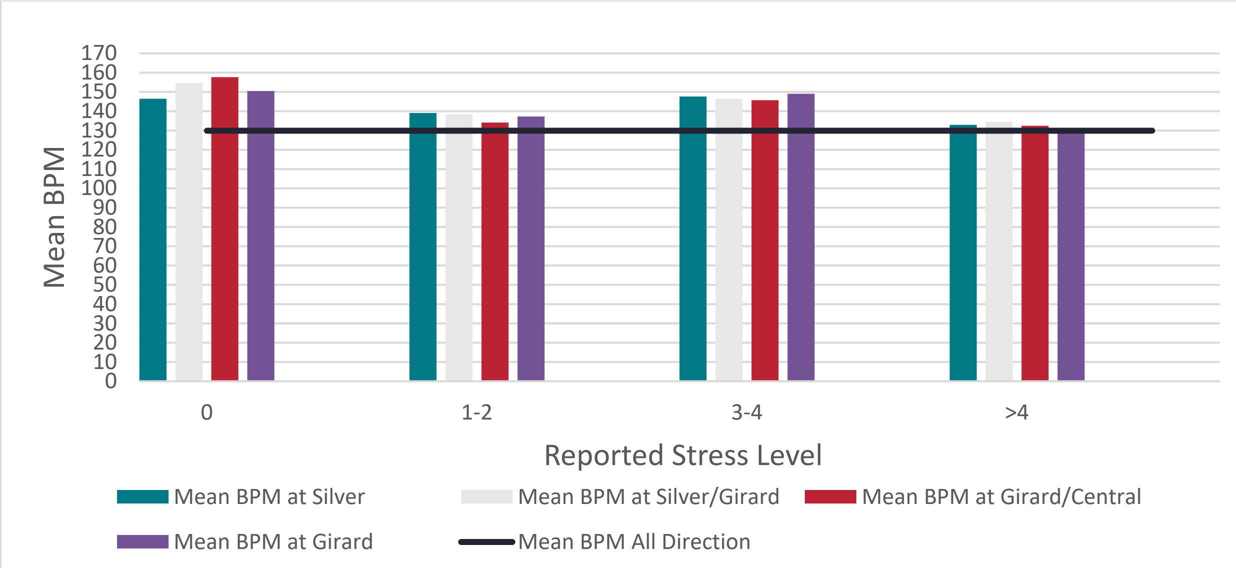


**Figure 16. Mean BPM at various intersections.**

Figure 16 also shows that the mean BPM at every intersection for subjects with different categories of reported stress levels is generally above the overall average BPM of riding sessions for all subjects. The only exception is at the Girard intersection, where the average BPM for subjects with a reported stress level of greater than 4 matches the overall mean BPM of riding sessions for all subjects, covering both directions. Similarly, with an increased BPM, it can be generalized that there is an increase in physical exertion or stress level. From this, it can be inferred that most subjects with different reported stress levels experienced more significant stress at intersections than the rest of the session.

Figure 17 displays the reported stress levels from the NASA TLX questionnaire and the mean BMP for each intersection, considering only the first direction of the ride each individual performed. In the figure, the mean BPM at every intersection for subjects with different categories of reported stress levels is generally above the overall average BPM of riding sessions for all subjects. The only exceptions are at the Girard intersection and Girard/Central intersection, where the mean BPM for subjects with a reported stress level of 1-2 and greater than 4, respectively, matches the overall mean BPM of riding sessions for all subjects in the 1st Direction of their riding session. Likewise, as BPM increases, there is an increase in the stress level or physical extortion, so there is an increase in stress level at most of the intersections for every subject with different reported stress during their riding session in 1st direction compared to the rest of the session.

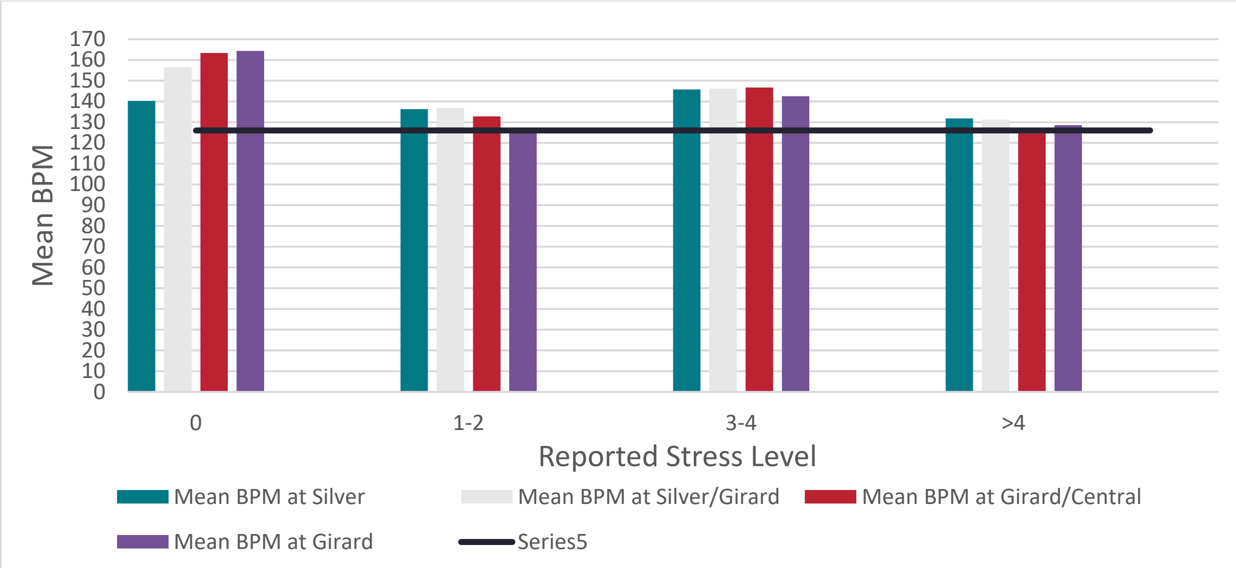


**Figure 17. Mean BPM at each intersection for 1st direction and reported stress level.**

Figure 18 displays the reported stress levels from the NASA TLX questionnaire and the mean BMP for each intersection, considering only the second direction of the ride each individual performed. The mean BPM at every intersection for subjects with different categories of reported stress levels is generally above the overall average BPM of riding sessions for all subjects. The only exceptions are at the Silver intersections and Girard intersection, where the mean BPM for subjects with a reported stress level greater than four matches the overall mean BPM of riding sessions for all subjects in the 2nd direction of their riding session. Additionally, for every intersection, the mean BPM for subjects with a reported stress level of 3-4 is below the overall mean BPM of riding sessions for all subjects in the 2nd direction of their riding session. Similarly, with an increased BPM, it can be generalized that there is an increase in physical exertion or stress level. From this, it can be inferred that most of the subjects with different reported stress levels, i.e., 0, 1-2, and greater than 4, experienced more significant stress at intersections compared to the rest of the session during their riding session in the 2nd direction. Whereas the subjects with reported stress levels, i.e. 3-4, experienced a lower stress level at every intersection compared to the rest of the session during their riding session in the 2nd direction.

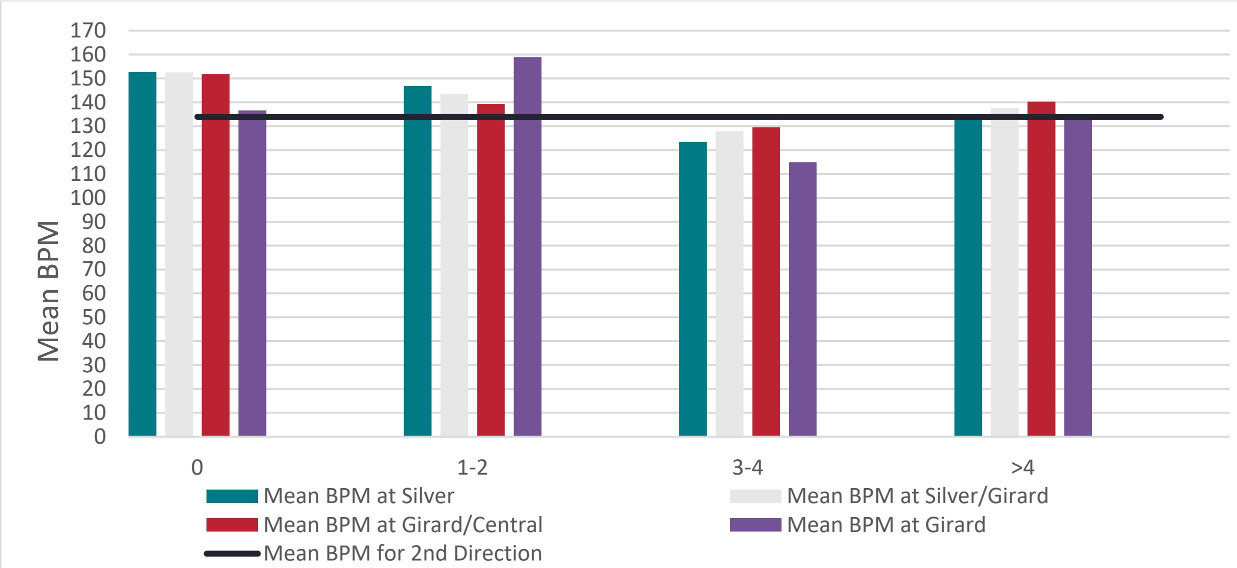


**Figure 18. Mean BPM at each intersection for 2nd direction and reported stress level.**

Figure 19 represents the BPM at different times during the riding session for a random single male subject. The X-axis represents the time (performance), and the Y-axis represents the BPM (physiological), which ranges from 0 to 180 BPM. The irregular line illustrates the subject's BPM fluctuations throughout the session. In contrast, the straight horizontal line signifies the mean BPM for the entire session. The grey-shaded area highlights the intersection area for the riding session, which represents 30 seconds before arriving at one intersection and 30 seconds departing from the other one. It is clear from the graph that the BPM at the intersection area is above the average BPM for the subject during the ride session. As the BPM increases, there is an increase in stress or physical extortion, so it can be inferred that the stress level around the intersection is higher than the other part of the route.

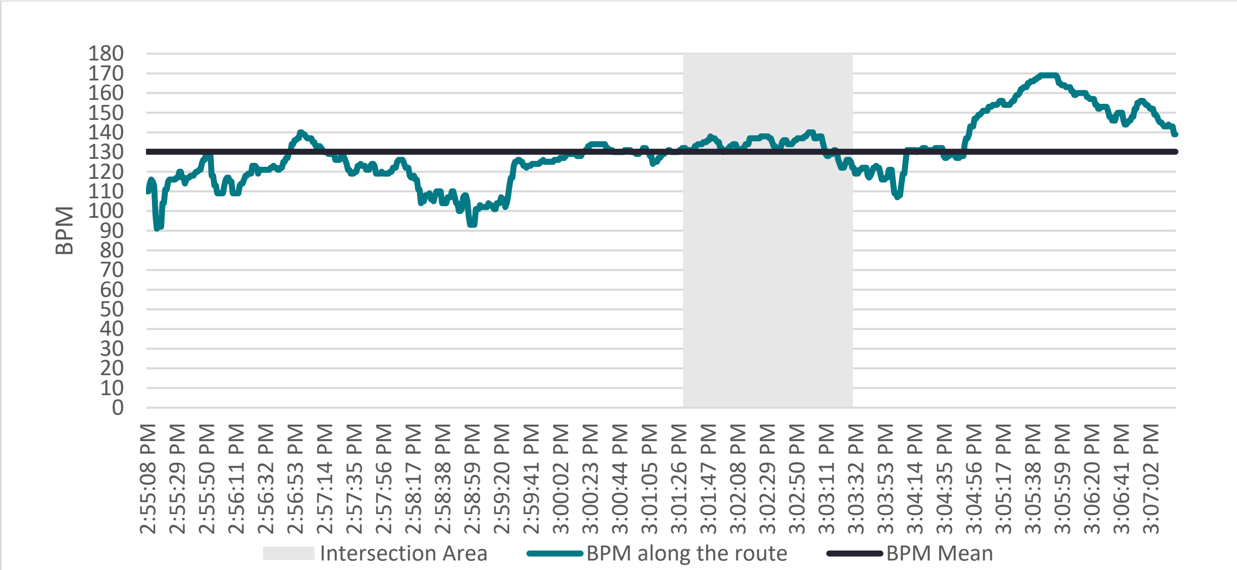


**Figure 19. BMP along a route on a single ride for a male subject**

Figure 19 and Figure 20 show that the BPM at the intersection area is above the average BPM for both male and non-male subjects during the ride session. As the BPM increases, there is an increase in stress or physical extortion, so it can be inferred that the stress level rises around the intersection and in the moments surrounding it compared to the whole riding session.

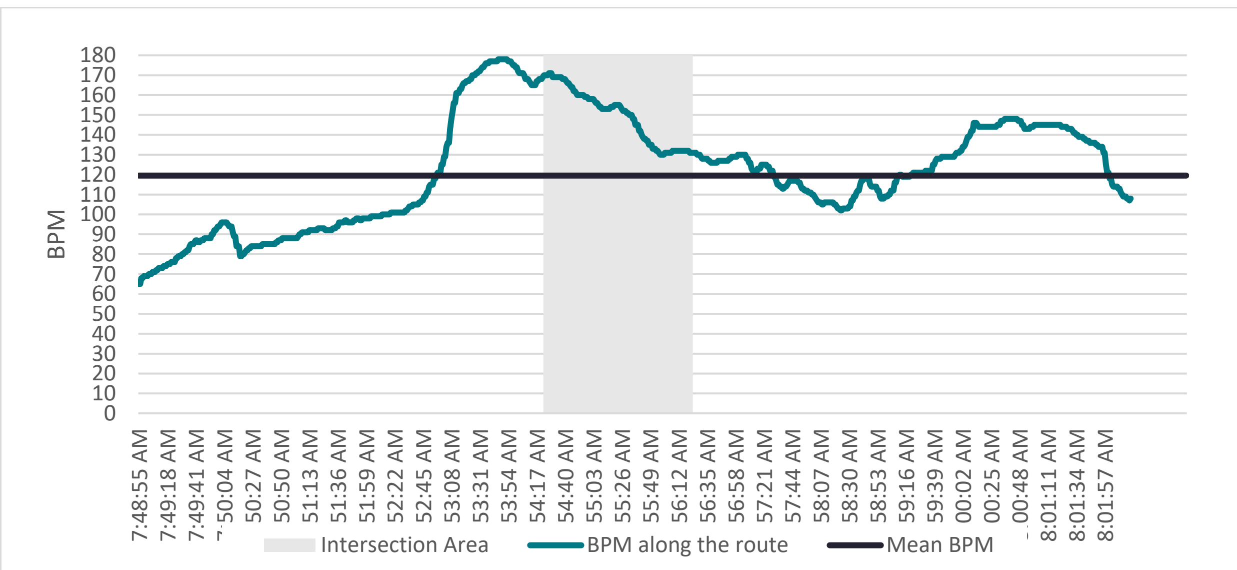


**Figure 20. BMP along a route on a single ride for a non-male subject**

Additionally, we used AOI heat maps to showcase areas where respondents were fixing their views during the same intersections considered above (physiological measure). For example, Figure 21 compares the Gerard/Central intersection for clockwise (CW) or south-north view and counterclockwise (CCW) rides or north-south view. In both scenarios, subjects primarily focus straight ahead and toward the lower light. This may be due to the riding position of cyclists, which makes the lower light more convenient. It appears that the direction of travel is not a significant factor for riders, as the heatmaps indicate a consistent focus regardless of direction. This is further supported by the heatmap of the Girard/Silver intersection (Figure 21, c), where riders predominantly look straight ahead. Although this heatmap cannot be directly compared with the others, it reinforces the idea that cyclists generally focus straight ahead on intersections, regardless of direction.


a)Girard/Central SN view (CCW) b)Girard/Central NS view (CW) c)Silver/Gerard WE view (CCW)

**Figure 21. AOI Heat Maps at Intersections**

Figure 22 and Figure 23 illustrate each intersection, broken down by direction and rider gender. In all three cases, we observe that the 16 male subjects have much narrower areas of focus, while the seven non-male riders exhibit a broader area of focus. Specifically, at the intersection of Girard and Silver, male riders primarily look straight ahead, whereas non-male subjects tend to look further into the intersection along their direction of travel.


a)Girard/Central SN view (CCW) b)Girard/Central NS view (CW) c)Silver/Gerard WE (CCW)

**Figure 22. AOI Heat Maps at Intersections for Male Subjects Only**


Girard/Central SN view (CCW) Girard/Central NS view (CW) Silver/Gerard WE view (CCW)

**Figure 23. AOI Heat Maps at Intersections for Non-male Subjects Only**

Finally, Figure 24 and Figure 25 present each intersection, broken down by direction and whether the ride was the first or second completed. Although the differences between the first and second rides are smaller compared to those between non-males and males, an interesting pattern emerges. At each intersection, the area of interest was consistently larger for riders on their second ride than for those on their first ride.


Girard/Central SN view (CCW) Girard/Central NS view (CW) Silver/Gerard WE view (CCW)

**Figure 24. AOI Heat Maps at Intersections for first ride**


Girard/Central SN view (CCW) Girard/Central NS view (CW) Silver/Gerard WE view (CW)

**Figure 25. AOI Heat Maps at Intersections for second ride**

Based on the literature, scanning while in motion is a stress response (Ryerson et al., 2021). However, to the author's knowledge, there have not been studies on scanning while at a signalized stop, which could not directly indicate a stress response, as cyclists likely feel some protection in this situation. Hence, further investigation is needed to draw definitive conclusions.

## Discussion

This section will present the results in two parts: the first will examine workload measures and the insights derived from the data collected in this study. The second subsection will analyze the data collection process, reflecting on lessons learned for future research utilizing naturalistic experiments and datasets to inform non-motorized infrastructure.

### Workload Measures

The subjective measures capture various aspects of cyclists' workload. Drawing on established scales such as NASA TLX and Borg RPE, the post-cycling survey assessed physical exertion, motivation, distraction, and mental demand. These multidimensional survey questions were evaluated for internal consistency using Cronbach's alpha. The indices reveal that subjects frequently engage in multitasking (MAAS). They do not find the task to be physically or mentally demanding (NASA TLX); however, they report high frequencies of heart and breathing rates, which could also serve as indicators of performance workload (Borg RPE).

Subjective measures also provide invaluable insights that objective measures cannot capture, such as age, collision history, route planning preferences, and educational level. This information is essential for understanding the relationship between cultural and socioeconomic factors and the decision-making processes and preferences of cyclists when planning and navigating infrastructure. It also enables measurement of subjects' comfort levels and frequency of cycling. However, a limitation of subjective measures is their inability to capture moment-to-moment data without disrupting the naturalistic setting. Therefore, it is crucial to complement these findings with objective measures to understand the outcomes derived from the subjective data fully.

Combining ECG and subjective measures, we observe the relationship between stress levels and mean BPM at various intersections along the route, providing valuable insights into the physiological impact of stress during riding sessions. Likewise, subjects experienced an increased BPM at specific periods, particularly around the intersections area. Furthermore, both graphs not only provide the information mentioned above but also have practical purposes. These analyses can be used to understand BPM for training optimization for long-distance cyclists and to identify stress triggers, such as certain maneuvers or terrains. Regarding safety and health monitoring, the graphs and analyses could help detect abnormalities and prevent overexertion. Similarly, these analyses hold practical purposes for research and development as well. By understanding how stress is related to BPM at various intersections, we can create a safer and more efficient road, which could also lead to safer commuting.

Eye tracking data can capture numerous variables, such as fixation points, saccades, and pupil dilation. This data is a powerful tool for creating heat maps that illustrate where cyclists focus their visual attention. Variables like the sequence, frequency, and duration of eye fixations provide insights into cyclists' scanning behavior and decision-making processes.

The eye-tracking data for this project highlight two intersections (Figure 4) located in segments with high BLOS. A consistent pattern emerged among riders, with most looking straight ahead at the intersection. However, when analyzing the data by gender, a different pattern was observed: males tended to look straight ahead, while non-males scanned the intersection more broadly. Several hypotheses could explain these observations, but further research is necessary to draw definitive conclusions. One possibility is that the broader area of focus among non-male riders is due to the smaller sample size, which could influence the aggregation results. Alternatively, non-male riders might exhibit broader focus due to higher stress levels, greater observational tendencies, or different levels of focus compared to male riders. To substantiate these hypotheses, further investigation into eye-tracking studies by gender is required. Additionally, comparing these observations with survey results might provide further insights. For example, non-male riders might report a higher mental workload or male riders might have more cycling experience, among other potential factors. What is evident from the heat maps is that non-male riders display a wider range of fixation points compared to male riders.

At each intersection, the area of interest was consistently larger for riders on their second ride than for those on their first ride. This may suggest that riders became more comfortable with the intersection on their second approach, even though they were coming from a different direction. For example, at the Central/Girard intersection, riders on their first attempt seemed to focus primarily on the signal, likely because the intersection was new to them, and they did not want to miss the light. On the second ride, however, riders were more likely to look around, being familiar with the lengthy light cycle yet still maintaining a forward focus overall. In terms of commuting, we can infer that increased exposure to an intersection leads to greater familiarity, prompting riders to look around more.

Combining eye-tracking data with survey results and ECG data offers a comprehensive understanding of cyclists' experiences. For example, an increase in stress levels captured by ECG, coupled with increased eye fixation, indicates a higher workload and a perception of unsafe infrastructure.

Another example of combining metrics involves subjective and physiological measures. Increased mental workload is often associated with longer eye fixations. High workload levels strongly correlate with decreased cycling speeds, as cyclists slow down to better scan and process their surroundings, thereby reducing the risk of errors. Additionally, higher physical demand is directly linked to increased heart rates. Distraction, another important factor identified in the survey, can be detected through eye-tracking data. These distractions and eye glances are crucial for ensuring the safety of all road users, as they are often implicated in collisions categorized as "looked but failed to see."

## Data Collection – Lessons Learned and Future Research

One of the key strengths of this study design is its high external validity due to conducting environmental research in real-world settings, although this approach also presents certain challenges (C. Neale et al., 2020). One significant lesson from this endeavor is the careful planning involved in purchasing the sensors. An unexpected situation arose when the GPS embedded in the ECG device stopped working. However, the pre-arranged use of a mobile GPS allowed for flexibility and continuity in the data collection process.

The authors engaged with various sellers to understand the capabilities of the sensors and the processing software each seller developed. This communication ensured that the sensors would meet the specific needs of the experiment, including considerations for cycling movements and sweating. Additionally, it was important to confirm that the sellers would provide technical support during the experiment. Another key lesson is the importance of ensuring all team members fully understood the experiment's procedures and could effectively communicate these to the participants. Sharing the experiment design with the biosensor sellers also proved beneficial, as it helped in selecting the most suitable sensors and gaining valuable insights from the manufacturers. Close collaboration with the sellers/manufacturers and efficient teamwork among the research team members were crucial for the successful data collection.

An additional key finding of this study is derived from the information gathered from the recruited participants. Despite informing participants that caffeine consumption or other habits might impact the measurements, at least one participant reported consuming a caffeinated beverage before the experiment. Furthermore, another participant disclosed having a heart condition but was also a frequent bicycle commuter. It is crucial to account for these unexpected outliers in future studies.

During the course of this project, it was observed that some subjects were wearing glasses, which appeared to impact the eye-tracking data. These subjects still had a significant number of tracking points, but they had fewer fixation points—often several hundred fewer compared to subjects not wearing glasses. For instance, subjects without glasses typically had over 1,000 fixations, whereas those with glasses might only have around 700. However, a subject wearing sunglasses had a number of fixations comparable to those of subjects not wearing any glasses, suggesting that the position of the eye tracker (whether placed before or after the glasses) might influence the results more than the mere presence of glasses. This discrepancy suggests potential interference caused by glasses, but it could also be attributed to other factors, warranting further investigation.

Moreover, although specific characteristics of the ride, such as start time, temperature, and wind speed, were recorded, these factors could influence the overall results of the study. For instance, these conditions might affect the amount of traffic present during the rides, potentially impacting the physiological and performance measures recorded in real-time. In future studies, the authors plan to utilize the recordings to monitor traffic volumes and assess their potential influence.

Additionally, upon reviewing the camera recordings, it was observed that certain subjects did not effectively communicate with their surroundings. Few participants performed shoulder checks before crossing intersections or signaling to vehicles or pedestrians. Despite being instructed to ride as naturally as possible, akin to a typical day, some participants resorted to using the sidewalk, even though they reported feeling highly safe riding their bikes in proximity to cars.

Referring back to Figure 3, subjects encountered five types of infrastructure: bike routes, buffered lanes, bike lanes, bike boulevards, and proposed bike routes/non-biking infrastructure. These infrastructure types could change along a single road section, raising issues discussed in the literature review session on factors impacting perception, workload, and behavior. From a cyclist's perspective, these infrastructure types offer little distinction, except for the noticeable difference between cycling infrastructure and the main roadway. Additionally, referring to Figure 5, subjects encountered multiple roadway LTS, and Figure 4 provides data on the BLOS for some sections. The data from this naturalistic study allows us to evaluate the differences in infrastructure types on cyclist stress and behavior, as well as the transitions between different infrastructure types. This data could also provide a quantitative measure to evaluate BLOS. By analyzing the ECG data along the route, research could determine if there is a significant difference in heart rate between infrastructure types, potentially indicating higher stress levels in certain types over others. Similarly, by evaluating the EEG data during transitions between infrastructure types, evidence could be found to corroborate whether different infrastructure types affect stress levels or if these changes are not noticeable to cyclists.

These findings are important for city planners, as they can inform which infrastructure types are preferred by cyclists or highlight that certain designations may be unnecessary from a cyclist's perspective. Additionally, by evaluating physiological data along the route, researchers can identify sections where stress is correlated with a BLOS of 1 or where no stress is identified, which may correlate with sections not being calculated. Since the route did not encounter any paths with a BLOS greater than 1, further investigation is needed to assess stress levels across various BLOS levels. Eye-tracking data could also be incorporated into these analyses, though producing fixation heat maps may be challenging. Alternative methods should be evaluated to determine if incorporating eye-tracking data would be beneficial. If producing fixation heat maps is feasible, similar methods applied to intersections could be applied to roadway sections and compared against the ECG data, noting that current literature suggests broader fixation patterns along sections are a stress response.

Finally, the data collected as part of this experiment is very complex, and combining capabilities is necessary for processing the data together. Hence, future research should consider purchasing biosensors that combine multiple sensors within a single device. This approach would minimize interference with the cycling task, which is particularly important in naturalistic studies where subjects need to maintain a natural feeling while cycling and have the freedom of movement necessary for exerting physical effort.

## Conclusions and Recommendations

This study highlights the importance of understanding the various factors influencing cyclists' mental workload, perception, comfort, and behavior. By combining subjective measures with physiological and eye-tracking data, we have gained a comprehensive understanding of cyclists' experiences and the impact of different infrastructural contexts on their performance and safety.

The cycling naturalistic experiment design incorporated subjective, performance, and physiological measures. These measures were selected to cross-validate and complement each other, ensuring optimal data collection. The sample of participants was carefully selected to represent the gender demographics of the US cycling population. The overall experimental route design included various types of intersections, such as signalized intersections, roundabouts, and stop signs, along with different road segments, including bike lanes and mixed lanes with vehicular traffic.

Our findings reveal that while cyclists may not perceive the task as physically or mentally demanding, physiological indicators such as heart and breathing rates suggest otherwise. The subjective data also shed light on the influence of cultural and socioeconomic factors on cyclists' route planning and decision-making processes. These insights underscore the necessity of integrating subjective and objective measures to fully capture the complexities of cyclists' experiences. The eye-tracking data provide valuable information on cyclists' visual attention and scanning behavior, particularly at intersections. Gender differences in visual attention patterns were observed, indicating that further research is needed to understand these differences and their implications for cycling safety.

Lessons learned from this study emphasize the importance of careful planning in sensor selection and the need for thorough communication with participants and team members. Future studies should consider using integrated biosensors to minimize interference with the cycling task and ensure more naturalistic data collection.

Despite the limitations, such as the inability of subjective measures to capture moment-to-moment data and the influence of unexpected outliers, this study provides a solid foundation for future research. By leveraging advanced technologies and naturalistic study designs, we can develop more comprehensive and accurate assessments of cyclist workload and safety. Ultimately, these insights can inform the design of safer and more enjoyable cycling environments, contributing to the broader goal of promoting active transportation and improving public health.

In conclusion, this study underscores the critical need for a holistic approach to understanding cyclists' experiences. By integrating multiple data sources and considering the diverse factors that impact cycling, we can enhance our knowledge and develop effective strategies to improve cycling infrastructure and safety. This research serves as a stepping stone for future studies aimed at making cycling a safer and more viable mode of transportation for all.

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# Appendix A Questionnaire Previous to the Experiment

Thank you for your interest in participating in this study. Responding to these questions will allow us to create a more robust analysis as part of our project. The questions are mainly related to your transportation habits and sociodemographic.

**SECTION 1 Socioeconomic and Demographic Questions**
Q1. What is your age? (Please indicate by writing your age in a numerical format, such as 38)

______

Q2. With which gender do you identify (or more closely identify)?

0. Male
1. Female
2. Non-binary/Third gender

Q3. What is the highest level of education that you have completed? *Please select one.*

0. Grade School
1. Some High School
2. Graduated High School
3. Some Colleges – no degree
4. Technical School or Vocational Training
5. Graduated College – Associate's degree
6. Graduated College – Bachelor's degree
7. Post Graduate Degree – MS, MA, MBA, MD, DVM, DDS, etc
8. Doctorate – Ph.D.

Q4. What best describes your ancestry or racial heritage? *Please select one.*

1- African/African-American
2- Asian
3- Caucasian / White
4- Indigenous Peoples (i.e. Native American, Pacific Islander, Aboriginal, Aleutian)
5- Prefer not to answer
6- Other

Q5. Are you Hispanic or Latino?

1. Yes
2. No

Q6. Including yourself, how many persons are in your household?
1- 1
2- 2
3- 3
4- 4
5- 5 or more

Q7. Do you have a U.S. driver's license or equivalent driver's license that allows you to drive in the U.S.?
1. Yes
2. No

Q8. How many accidents have you experienced while driving a car in the last three years?
1- 0
2- 1
3- 2
4- 3
5- 4 or more
6- I have not been driving the last three years

Q9. How many accidents have you experienced while riding a bike in the last three years?
1- 0
2- 1
3- 2
4- 3
5- 4 or more
6- I have not been driving the last three years

Q10. What is your current marital status? *Please select one.*
a. Never Married/Single
b. Living with partner
c. Married
d. Separated
e. Divorced
f. Widowed

**SECTION 2 Travel Habits & Micromobility**

Q11. Which of the following is your primary mode of travel (used in most trips or more often than other modes and/or used for most of the distance) <u>for each</u> trip purpose listed below? *(Please select only one mode for each trip purpose listed below).*

| | Walk (1) | Bike (2) | Drive alone (car/motorcycle, etc.) (3) | Others (4) |
|---|---|---|---|---|
| Work/School (1) | | | | |
| Grocery and other shopping (2) | | | | |
| Personal business (such as errands) (3) | | | | |
| Social/recreational (4) | | | | |

Q12. During your typical out-of-home travel week l, how many trips did you take for the following purposes using any mode or combination of modes of travel (including but not limited to walking, cycling, driving, carpooling, public transportation, etc.)?

***Note:*** A trip is defined as a single journey between no more than two destinations for a specific purpose (for example, taking a bus to work, cycling to the grocery store, walking to a restaurant, or driving to a park and ride and riding the metro to work, etc.).

| | 0 (0) | 1 (1) | 2-3 (2) | 4-5 (3) | 6-7 (4) | 8 or more (5) |
|---|---|---|---|---|---|---|
| Work/School (1) | | | | | | |
| Grocery and other shopping (2) | | | | | | |
| Personal business (such as errands) (3) | | | | | | |
| Social/recreational (4) | | | | | | |

Q13. Do they consider the time of day when you cycle or use an e-scooter?

0. Yes
1. No
2. Sometimes

Q14. Do you consider the weather when deciding when to cycle or use an e-scooter?
1- Yes
2- No
3- Sometimes

Q15. How likely are you to listen to music with headphones while riding a bike or e-scooter?
1- Very unlikely
2- Unlikely
3- Neutral
4- Likely
5- Very likely

Q16. How likely are you to listen to music with a speaker while riding a bike or e-scooter?
1. Very unlikely
2. Unlikely
3. Neutral
4. Likely
5. Very likely

Q17. How likely are you to talk to other cyclists/passengers/pedestrians on your route?
1. Very unlikely
2. Unlikely
3. Neutral
4. Likely
5. Very likely

Q18. How likely is it that you would ride micromobility devices in the following infrastructure:

| | Very Unlikely (1) | Unlikely (2) | Neutral (3) | Likely (4) | Very Likely (5) |
|---|---|---|---|---|---|
| A route with a cycle path | | | | | |
| The route with the least traffic | | | | | |
| A smooth surface on the cycle path/road | | | | | |
| A most direct route | | | | | |

| | | | | | |
|---|---|---|---|---|---|
| The presence of signalized crossings | | | | | |
| The fastest route | | | | | |
| Marked cycle/e-scooter lanes in the crossings | | | | | |
| Good street lighting | | | | | |

**SECTION 3. Personality Statements from Maas**

Q19. How much would you agree with the following statements:

| | Strongly Disagree (1) | Disagree (2) | Neutral (3) | Agree (4) | Strongly Agree (5) |
|---|---|---|---|---|---|
| I find it difficult to stay focused on what's happening in the present. | | | | | |
| I tend to walk quickly to get where I'm going without paying attention to what I experience along the way. | | | | | |
| I do jobs or tasks automatically, without being aware of what I'm doing. | | | | | |
| I find myself listening to someone with one ear, doing something else at the same time. | | | | | |
| I drive places on 'automatic pilot' and then wonder why I went there. | | | | | |
| I find myself doing things without paying attention. | | | | | |

Q20. How satisfied are you with your health?

0. Very dissatisfied
1. Dissatisfied
2. Neutral
3. Satisfied
4. Very satisfied

## Appendix B Questionnaire Previous to the Experiment

Thank you for participating in this study. This last questionnaire would assess subjectively your perceptions about the activity you just performed.

**SECTION 1 NASA TLX**

Q1.Please rate the following statements:

| | | 1 | 2 | 3 | 4 | 5 | 6 | 7 | |
|---|---|---|---|---|---|---|---|---|---|
| How mentally demanding was the task? | Very Low | | | | | | | | Very High |
| How physically demanding was the task? | Very Low | | | | | | | | Very High |
| How hurried or rushed was the pace of the task? | Very Low | | | | | | | | Very High |
| How successful were you in accomplishing what you were asked to do? | Perfect | | | | | | | | Failure |
| How hard did you have to work to accomplish your level of performance? | Very Low | | | | | | | | Very High |
| How insecure, discouraged, irritated, stressed, and annoyed were you? | Very Low | | | | | | | | Very High |

**SECTION 2 Other Workload Questions**

Q2. Did you feel safe due to the proximity of cars?

4- Strongly Agree - I felt very safe due to the proximity of cars.
5- Agree - I felt safe due to the proximity of cars.
6- Neutral - I neither felt safe nor unsafe due to the proximity of cars.
7- Disagree - I felt unsafe due to the proximity of cars.
8- Strongly Disagree - I felt very unsafe due to the proximity of cars.

Q3. Did you feel safe due to the volume of cars?

1- Strongly Agree - I felt very safe due to the volume of cars.
2- Agree - I felt safe due to the volume of cars.
3- Neutral - I neither felt safe nor unsafe due to the volume of cars.
4- Disagree - I felt unsafe due to the volume of cars.
5- Strongly Disagree - I felt very unsafe due to the volume of cars.

Q4. How fast are you breathing?
1. Very Slow - My breathing is very slow and steady.
2. Slow - My breathing is slow but steady.
3. Normal - My breathing is at a normal pace.
4. Fast - My breathing is faster than usual.
5. Very Fast - My breathing is very fast and rapid.

Q5. How fast is your heart beating?
1. Very Slow - My heart beating is very slow and steady.
2. Slow - My heart beating is slow but steady.
3. Normal - My heart beating is at a normal pace.
4. Fast - My heart is beating faster than usual.
5. Very Fast - My heart beat very fast and rapidly.

Q6. How tired are your muscles?
0. Not tired at all - My muscles feel fresh and rested.
1. Slightly tired - My muscles feel a little fatigued, but I can still perform activities without much difficulty.
2. Moderately tired - My muscles feel noticeably fatigued, and I may experience some discomfort during physical activities.
3. Very tired - My muscles feel quite tired, and it's challenging to perform physical tasks.
4. Extremely tired - My muscles feel completely exhausted, and even simple movements are difficult.

Q7. How much are you sweating?
- Not sweating at all - I am not sweating or perspiring.
- Very little - I am sweating minimally, if at all.
- Moderate - I am sweating moderately, but it is not excessive.
- Considerably - I am sweating noticeably, and my clothes may feel damp.
- Profusely - I am sweating heavily, and it is dripping or running down my body.