DISSERTATION

EVALUATING MICROMOBILITY ADOPTION, PERCEPTION, AND IMPLEMENTATION

Submitted by

Shiva Pourfalatoun

Department of Systems Engineering

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Doctoral Committee:

Advisor: Erika Gallegos

Jeremy Daily
Steve Simske
Thomas Bradley
Ziyu Jin

ABSTRACT

EVALUATING MICROMOBILITY ADOPTION, PERCEPTION, AND IMPLEMENTATION

Micromobility, a term that encompasses compact and efficient transportation modes such as bicycles and scooters, has rapidly emerged as an important element of urban mobility. These small, often electrically-powered vehicles offer a versatile solution to urban congestion and provide an eco-friendly alternative to traditional transportation modes. Particularly, shared bicycles and e-scooters have become popular due to their convenience and accessibility, offering significant benefits but also presenting new challenges in urban planning and traffic management. This transition in urban transport paradigms raises several pertinent questions about user behaviors, preferences, and the interplay of various socio-psychological factors. This dissertation aims to explore three key aspects of micromobility. The first research question investigates the differences between shared e-scooter users and non-users, along with the factors influencing their decisions regarding e-scooter usage. The second question examines the shift in micromobility preferences and perceptions before, during, and after the COVID-19 pandemic, focusing on how these changes correlate with different quarantine behaviors. The third and final question delves into the interactions between drivers, bicyclists, and pedestrians, analyzing how drivers' risk-taking propensity and emotional intelligence influence these interactions. Each of these questions is approached through specific methodological frameworks, employing a mix of statistical analyses and behavioral observations to provide insights into the evolving dynamics of urban mobility. The findings from this research provide a systematic approach to integrating micromobility, by understanding at the individual level the factors that effect decision-making on usage, as well as interaction effects with other road users that impact safety.

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DEDICATION

To the pursuit of knowledge,

May it serve as a humble contribution to the power of curiosity in our shared pursuit of wisdom.

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Chapter 1

Introduction

Micromobility, encompassing various small, lightweight, and often electrically powered vehicles like bicycles and scooters, has gained significant traction in urban transportation systems globally (Reck & Axhausen, 2021). Shared bicycles and e-scooters play a vital role in promoting sustainable urban mobility. These modes of transport offer numerous benefits, including reducing traffic congestion, providing a green alternative for short trips, and improving overall urban mobility (Bieliński & Ważna, 2020).

The introduction of electric scooters has notably impacted urban transportation, capturing a substantial portion of the micromobility market in cities worldwide (Bloom et al., 2021). The popularity of these transportation modes continues to grow as cities around the world embrace these innovative transportation solutions to address the challenges of urbanization and climate change (Szell, Mimar, Perlman, Ghoshal, & Sinatra, 2022). Moreover, shared micromobility services, such as electric bicycles and scooters, have been shown to influence passengers' travel decisions and behaviors, indicating a shift towards more sustainable and efficient transportation options (Szell et al., 2022). As micromobility continues to evolve, research focusing on user behaviors, safety considerations, and the integration of these modes into existing transportation systems becomes essential.

As urbanization increases, transportation systems and networks face heightened challenges related to capacity constraints. Emerging technologies in transportation offer new opportunities to address these challenges, as existing systems and networks likely cannot meet these increasing demands (de Bortoli & Christoforou, 2020). With the ongoing evolution of urban environments, understanding the implications of these micromobility modes on urban mobility, safety, and sustainability is crucial for developing effective policies and infrastructure to better support their integration into urban landscapes. This dissertation seeks to answer pivotal questions that can inform better decision-making and contribute to more resilient urban transport systems.

1.1 Research Questions

This work is split into three research questions, each with their own methodology. These research questions are described as follows.

Research Question 1: What are the differences between shared e-scooter users and non-users, and what factors influence their decisions to use or not use shared e-scooters?

Method: A survey study was conducted to investigate the differences between shared e-scooter users and non-users, and to understand the factors influencing their decisions to either use or avoid these services. Participants were categorized based on their use of shared e-scooters, where individuals who reported using a shared e-scooter at least monthly were classified as 'users,' while those who had never used a shared e-scooter were classified as 'non-users.' All participants were required to be at least 18 years old and residents of Colorado. The analysis utilized 409 complete responses. Statistical significance was assessed at $\alpha = 0.05$. To compare users and non-users, binary logistic regression, chi-squared tests, Cochran's Q tests, and McNemar tests were performed.

Research Question 2: How did preferences and perceptions of micromobility change before, during, and after the pandemic, and in relation to quarantine behaviors?

Method: Shared electric scooter trip data (N = 2,604) and survey data (N = 134) was collected and analyzed to explore changes in micromobility preferences and perceptions before and during the pandemic, and relative to quarantine behavior. Electric scooter trip data was provided by a shared micromobility company, who provided two weeks of trip data: pre-pandemic (January 25-31, 2020) and during-pandemic (January 25-31, 2021). A different survey than the one used in RQ1 was performed for this study. Survey participants were divided into three groups based on their quarantine activities: Group 1 (27.0%) consisted of participants who continued to leave their house similarly to pre-pandemic times; Group 2 (24.0%) included those who only left their house for essential activities; and Group 3 (49.0%) encompassed those who left for essential activities and work. Statistical significance was assessed at $\alpha = 0.05$. Analysis of variance (ANOVA) tested differences in trip durations and counts before and during the pandemic, with Tukey's Honest Significant Difference (HSD) test for pairwise comparisons. ANOVA was selected for its robustness in identifying significant differences between groups while controlling for variability within the dataset, making it an ideal method for assessing changes in micromobility behavior before, during, and after the pandemic. Fisher's exact test was employed to identify variations in travel behavior between the three quarantine groups. This statistical method is particularly well-suited for analyzing associations between categorical variables, especially when expected frequencies in contingency tables are low. In this study, the number of participants in certain travel behavior categories within each quarantine group may have been relatively small, making Fisher's exact test a more appropriate choice than the chi-squared test. Chi-square tests were used to evaluate mode choice differences across the pandemic stages.

Research Question 3: How does risk-taking propensity and emotional intelligence of drivers impact their interactions with bicyclists and pedestrians?

Method: A driving simulator study was conducted to explore the impact of risk-taking propensity and emotional intelligence on driving behaviors towards micromobility users. There were 40 participants that completed this study. Each participant navigated through urban streets, encountering various scenarios: three passing events involving single bicyclists on the road, three passing events of single bicyclists in the bike lane, three passing events of a group of bicyclists in the bike lane, and one mid-block pedestrian crossing. Drivers' Emotional intelligence (EI) and risk-taking were assessed using two surveys: the first, a 30-question EI survey adapted from the TEIQue-SF (Cooper & Petrides, 2010) for driving contexts, and the second, post-drive, focused on demographics and general driving experiences including interactions with bicyclists and risk propensity measured by the GRiPS (D. C. Zhang, Highhouse, & Nye, 2019). To analyze driving behaviors, linear mixed models with random effects accounting for the multiple observations per participant, were used to predict speeds during bicycle interaction events. Additionally, binary logistic regression was used to model braking behaviors in pedestrian interaction events. Chi-squared tests assessed differences in post-drive survey responses across various risk groups, further clarifying the relationship between risk-taking, emotional intelligence, and driving patterns.

Chapter 2

Background

Concerns about the current transportation system, such as global climate change, energy security, unstable fuel prices, and capacity constrained networks, have prompted many experts around the world to consider the need for more sustainable strategies. Shared micromobility is a key strategy that could help address many of these concerns (Shaheen, Guzman, & Zhang, 2012). Specifically, micromobility has emerged as a viable and sustainable alternative to diversify mobility, as it can reduce traffic congestion, improve air quality, and help decarbonize the transportation fleet (Gubman, Jung, Kiel, & Strehmann, 2019; DuPuis, Griess, & Klein, 2019). This chapter summarizes relevant literature on micromobility and identifies important research gaps that this dissertation seeks to address.

2.1 Micromobility Definition

A micromobility device is a low speed, lightweight device intended for short-distance trips, such as a bicycle, scooter, or skateboard. These devices can be human-powered or electric, and they can be personally owned or publicly shared (Reck, Haitao, Guidon, & Axhausen, 2021).

In recent years, dockless and docked micromobility services (e.g., shared bicycles and shared electric scooters, e-scooters) have been deployed in many cities across the globe (Abduljabbar, Liyanage, & Dia, 2021). Demand for these devices is high (Lee, Chow, Yoon, & He, 2021; Tuncer & Brown, 2020). However, due to the recent and rapid growth of this technology, problems related to regulation, planning, and adoption remain unsolved (Fournier et al., 2020; Qian, Jaller, & Niemeier, 2020). Considering this growth of shared micromobility services, it is essential to explore and understand people's perceptions toward these relatively new modes of transport.

2.2 Evolution of Shared Micromobility Systems

The first public shared micromobility reported was a bike sharing system in 1965 in Amsterdam, Netherlands. This concept has since expanded to other cities across Europe, and later into North America (Parkes, Marsden, Shaheen, & Cohen, 2013). The evolution of shared micromobility has been categorized into four key phases (or generations). The first generation called 'White Bikes,' offered free bicycles throughout Amsterdam; the second generation was characterized by a coin-deposit system in which bicycles were located at designated stations with locks; the third generation was characterized by an information technology (IT) system with theft deterrents and smart technology to track user's location data, however, users still had to return bicycles at fixed stations, otherwise, extra charges incurred. In order to provide a better and more advanced user demand responsive system, the fourth generation was introduced, featuring a dockless system, in which users could transfer bicycles and the newly introduced e-scooters at various and unfixed locations. This fourth generation addressed many of the previous generation's problems by providing a robust IT system and incorporating mobile docking stations which facilitated a spatio-temporal distribution of dockless ride-share devices (Shaheen et al., 2012; Abduljabbar et al., 2021). This dockless framework extended its market to North America in 2017, and continues to gain significant dissemination globally (Lee, Chow, Yoon, & He, 2019; Tuncer, Laurier, Brown, & Licoppe, 2020).

Dockless micromobility, in particular, has been rapidly growing across cities. For example, in the US, dockless services went from practically none in 2017 to accounting for over 38.5 million trips in 2018 (Younes, Zou, Wu, & Baiocchi, 2020; Arias-Molinares, Julio, Garcia-Palomares, & Gutierrez, 2021). However, literature has not kept pace with these trends, and dockless services remain largely under researched in comparison to docked services (Arias-Molinares et al., 2021). Moreover, one of the more rapidly growing micromobility services is the e-scooter, which are deployed and were introduced under the dockless service model. In 2022, dockless e-scooters were available in 158 cities across the US, a rise from 0 cities in 2017 and 58 cities in 2018 (of Transportation Statistics (BTS), n.d.).

2.3 Benefits of Shared Micromobility Systems

Urban populations around the globe are rapidly growing and are expected to account for more than half of the world's population by 2050 (Nations, 2019). As urbanization increases, transportation systems and networks face heightened challenges related to capacity constraints. Emerging technologies in transportation offer new opportunities to address these challenges, as existing systems and networks likely cannot meet these increasing demands. For example, Barajas and Brown (2021) highlighted the current gaps in access (i.e., coverage and frequency) to public transit, resulting in limited access to jobs, healthcare and/or education, which is disproportionately experienced by lower income, minoritized individuals. To address these coverage gaps and the growing demands on transportation systems, novel solutions and improvements to current infrastructure are needed.

Shared micromobility is considered a key strategy in addressing global climate change, energy security, and capacity constraints, particularly in increasingly dense urban areas (Shaheen et al., 2012; Shaheen, Bansal, Chan, & Cohen, 2017). As one of the most environmentally friendly modes of transportation, micromobility can help reduce traffic congestion and emissions (Wang & Zhou, 2017; Y. Zhang & Mi, 2018). Recent research has shown that electric scooters and bicycles reduce automobile usage and emissions in cities, while increasing mobility (Zagorskas & Burinskienė, 2020). These shared micromobility services can particularly improve mobility for [urban] residents in areas with limited transit service (Javadinasr et al., 2022). As such, micromobility offers a low-carbon solution for first/last mile and other existing gaps in transportation networks.

Overall, the main benefits of micromobility include increased mobility options, cost-efficient and time-saving alternatives, reduced traffic congestion, reduced fuel consumption, increased long-term health benefits, and increased environmental awareness (Shaheen et al., 2012; Shaheen, Cohen, Chan, & Bansal, 2020).

While it is believed that micromobility can minimize climate change impacts through reduced traffic congestion and pollution (Brown, Klein, Thigpen, & Williams, 2020; Gössling, 2020), this novel, shared mode of transport may also have unanticipated effects on the transportation network.

2.4 Safety of Shared Micromobility Systems

A key issue in the use of micromobility is that of user safety. According to a survey conducted in Greece, safety is one of the most important concerns for both users and non-users of micromobility, and that safety concerns are one of the main reasons why non-users do not use micromobility (Nikiforiadis et al., 2021). In recent years there has been a growing number of crashes involving e-scooters and e-bicycles. This rise in crashes has been observed through the use of questionnaires (Comer et al., 2020), news reports, and mobile sensing data (H. Yang et al., 2020; Ma et al., 2021). Moreover, scooter rental companies have historically not sufficiently promoted user safety, and the number of crashes is going up drastically (Dormanesh, Majmundar, & Allem, 2020).

In 2019, a study interviewed 125 e-scooter riders about safety concerns related to their riding experiences. Of the riders interviewed, 50% believed that poor surface conditions (such as a pothole or crack) contributed to injuries, 29% admitted that they had been influenced by alcoholic beverages prior to their injuries, and 37% reported that excessive speeds contributed to their injuries (Ma et al., 2021). In another study conducted in 2019, a survey was performed to understand the safety and travel behavior perception of 181 e-scooter riders and non-riders; the study indicated that improper parking of e-scooters was a significant safety concern for pedestrians (James, Swiderski, Hicks, Teoman, & Buehler, 2019).

E-scooter users are especially susceptible to trauma from falls given the ergonomics of an e-scooter, in particular their expedient nature and the absence of protective gear (Trivedi et al., 2019). A survey of 439 participants in Saudi Arabia reported that the majority (82%) of respondents who had previously used an e-scooter believed they were safe, whereas only a minority (18%) considered them unsafe (Almannaa et al., 2021). Similarly, a survey study in Italy indicated that electric micromobility users consider these devices fun and easy to use, while more broad public opinion perceives them as unsafe and dangerous (della Mura, Failla, Gori, Micucci, & Paganelli, 2022).

E-scooter users often rely on GPS navigation applications to guide them through unfamiliar urban environments. While these applications can provide real-time directions, they also introduce a set of challenges. Users may need to frequently check their devices to ensure they are on the correct route, which can lead to a fragmented travel experience. Research indicates that navigation-related distractions can significantly impair a user's ability to maintain situational awareness, increasing the risk of accidents (Krier, Chrétien, Lagadic, & Louvet, 2021). Users who feel confident in their ability to navigate may be more likely to adopt e-scooters as a regular mode of transport. Conversely, those who experience difficulties with navigation may be deterred from using e-scooters altogether. A survey conducted by the National Association of City Transportation Officials (NACTO) found that 41% of e-scooter users reported concerns about navigating safely in traffic (Dias, Ribeiro, & Arsenio, 2024).

The act of checking GPS navigation while riding an e-scooter can be particularly distracting. Even with a phone mount, users may find it difficult to glance at their devices without diverting their attention from the road. A study found that cognitive distractions, such as navigating with a smartphone, can lead to slower reaction times and decreased control over the vehicle (Fearnley, 2022). This is especially concerning in urban environments where e-scooter riders must navigate around pedestrians, cyclists, and vehicles.

In order to address these growing concerns, several cities have begun to develop guidelines and policies for micromobility companies to follow, such as acceptable operating speeds, a minimum age for use, organized parking areas, permitted operation locations, and helmet requirements (Gössling, 2020; de Bortoli & Christoforou, 2020). Despite this, the majority of local authorities have not prepared necessary regulations in order to integrate e-bikes/e-scooters efficiently and effectively (Chang, Miranda-Moreno, Clewlow, & Sun, 2019). To ensure the safe use of micromobility, it is important to examine the factors that are of concern to both users and non-users, such as the perceptions and individual factors that influence their decisions regarding micromobility use.

2.5 Demographics of Micromobility Users

Several studies have evaluated how user demographics effect shared micromobility ridership. Sanders, Branion-Calles, and Nelson (2020) found that non-white non-riders were more willing to try e-scooters than white non-riders and that women were more likely to report safety as a barrier to using e-scooters. In Vienna Austria, Laa and Leth (2020) surveyed 166 e-scooter users and found that most users of e-scooters are young men with high levels of education (Laa & Leth, 2020). Whereas Raptopoulou, Basbas, Stamatiadis, and Nikiforiadis (2020) noted that although the percentage of women using shared e-bikes/e-scooters is almost similar to that of men, men are more likely to use shared e-bikes/e-scooters compared to women. It has also been identified that most users of micromobility are between the ages of 25-34 and that most would have used a ride-hailing service had a shared e-bike/e-scooter been unavailable (San Francisco Municipal Transportation Agency, 2019). Similarly, it has been reported that shared e-scooters mostly attract people under the age of 40 (Baltimore City Department of Transportation, 2019; City of Santa Monica, 2019). Using data collected from companies in Austin Texas, a study reported that students comprise a large portion of all e-scooter rides (Caspi, Smart, & Noland, 2020).

It has also been reported that younger riders of e-scooters are more likely to engage in risky behaviors (Gioldasis, Christoforou, & Seidowsky, 2021; Pazzini et al., 2022). It is important to note, however, that gender differences in risky behaviors vary depending on the domain of behavior (Byrnes, Miller, & Schafer, 1999). For example, Gioldasis et al. (2021) analyzed data in Paris, France and found that male e-scooter riders were more likely to engage in risky behavior than female riders, including riding after drinking alcohol, using drugs and riding while using a mobile device. In contrast, a survey of 210 e-scooter users in the US found that females were more likely to engage in risky behaviors, such as riding on the sidewalk (Tian, Ryan, Craig, Sievert, & Morris, 2022). Meanwhile, a study in Norway reported no difference in risky behaviors between male and female riders when analyzing the speed of e-scooters (Gioldasis et al., 2021).

2.6 Micromobility Trip Purposes

Often, rider type is used to predict trip type. A recent meta-analysis on bike share revealed that casual users are more likely to use bike share for leisure purposes, while subscribers are more likely to use bike share for work trips (Fishman, 2016). Similarly, a study in Washington, D.C.

found that member bike sharing is typically used for work trips, while casual bike sharing and e-scooters are more used for leisure, recreation, and tourism trips (McKenzie, 2019).

Several studies have investigated the trip behaviors of e-scooter users specifically. A study in Munich, Germany (Sellaouti, Arslan, & Hoffmann, 2020) and another study in Vienna, Austria (Laa & Leth, 2020) both revealed consistent results, that e-scooters mostly replace walking and public transport trips. Sanders et al. (2020) similarly reported that e-scooters often replace walking trips, but conversely found that e-scooters are used for mandatory trip purposes rather than for recreation. Interestingly, a study in the state of Virginia found that e-scooter riders notice paths blocked by e-scooters significantly less often than other road users (21% of e-scooter users vs. 75% of non-users) (James et al., 2019).

The role of e-scooters in urban transport has gained significant attention as cities seek to address mobility challenges and promote sustainable transportation options. In urban areas, e-scooters often serve as an effective first- or last-mile solution, facilitating access to public transportation. Research indicates that dockless e-scooters can enhance the use of public transport by bridging the gap between transit stops and users' final destinations, thereby promoting a modal shift towards more sustainable transport options (Krier et al., 2021). For instance, in Oslo, e-scooter usage has been shown to replace public transport trips, particularly in areas with longer distances and car restrictions (Fearnley, 2022). This suggests that e-scooters can complement existing public transport systems by providing additional mobility options that are particularly valuable in dense urban environments.

Geographical variations also play a crucial role in how e-scooters fit into urban transport systems. In cities with high population density and limited parking, e-scooters can effectively alleviate traffic congestion and enhance public transit usage (Namiri et al., 2020). Conversely, in areas where car ownership is prevalent, e-scooters may struggle to replace existing modes of transport, as users may prefer the convenience of personal vehicles (Elhenawy et al., 2024). Furthermore, the integration of e-scooters into public transport systems is influenced by factors such as land use, weather conditions, and urban infrastructure, which can vary significantly across different geographical contexts (Zhao, Li, & Mansourian, 2024).

Many of these previous studies evaluate survey or trip data, but few consider both data sources for the same city as this dissertation does.

2.7 Infrastructure to Support Shared Micromobility Systems

The recent and rapid growth of shared micromobility services and, in particular e-scooters, has given city planners and engineers little time to evaluate and assess the impact on the existing infrastructure and the necessary safety measures to meet user needs (Cohen & Shaheen, 2021). E-scooters face the challenge of navigating a city in an environment that often prioritizes motor vehicles on the road, leaving little room for other road users in many areas. As a result, traveling through a city on an e-scooter can be unpleasant and dangerous at times, limiting the safe and sustainable adoption of these devices.

Moreover, the nature of the device leaves e-scooter users physically unprotected, as there is no crumple zone, meaning that users are likely to suffer serious injuries if a crash occurs with a vehicle (Karpinski, Bayles, & Sanders, 2022). Similarly, the lack of infrastructure for e-scooters also leads to potential conflicts with pedestrians, as e-scooter users often weave between the sidewalk and shoulder of the road (Tuncer & Brown, 2020; Ruhrort, 2020). In addition, the high center of gravity of e-scooters and their smaller wheels make them less stable (Ma et al., 2021), potentially leading to adverse outcomes during conflicts. Hence, there are serious barriers to the adoption of e-scooters, due to their perceived and real safety risks (Pucher & Buehler, 2017).

According to previous research, shared e-scooters create a service that meets the mobility needs of areas without a well-developed public transit system, as well as providing a fun means of transportation for adults (Nikiforiadis et al., 2021; Lee et al., 2021). Their rapid and massive rate of acceptance has also been attributed to the fact that younger individuals tend to prefer mobility options priced based on frequency of use, rather than purchasing for private ownership (Kostareli, Basbas, Stamatiadis, & Nikiforiadis, 2020).

Hosseinzadeh, Karimpour, and Kluger (2021) explored the use of e-scooters in Louisville, Kentucky, and found that areas with increased walk-ability and bike-ability are most preferred by e-scooter riders, indicating that most active and micromobility modes favor a similar kind of environment (Hosseinzadeh, Algomaiah, Kluger, & Li, 2021). Data from Austin, Texas shows that areas of larger e-scooter usage are at the university campus, and in downtown Austin, where there is high population and activity density (Jiao & Bai, 2020).

2.8 COVID-19 Pandemic Impact on Shared Micromobility

As a result of the COVID-19 pandemic that began in 2020, travel behavior and mode choices have changed (Almannaa et al., 2021). Cities in the U.S. reported a decrease in shared micromobility commutes during COVID-19 (Hosseinzadeh, Karimpour, & Kluger, 2021). For example, a study in New York City in 2020 reported that bike share decreased by 71% and subway trips by 90% as compared with the previous year before the pandemic (Teixeira & Lopes, 2020; Jobe & Griffin, 2021). However, this can likely be attributed to an overall decrease in trips taken during the pandemic, especially due to the lockdown orders and shift to remote working and distance education. In fact, many studies have shown people switching from public transport modes to shared micromobility modes. A public survey in Australia revealed a significant increase in the number of bicycle rides and a switch from public transport to cycling as a mode of transportation (Lock, 2020). Another case study in Zurich, Switzerland, found that employees who did not work remotely were more likely to switch to micromobility to avoid public transport modes during the pandemic (Li, Zhao, He, & Axhausen, 2020). A survey study in San Antonio, Texas by Jobe and Griffin (2021) found that on average, people reported a higher intent to use bike share after the COVID-19 restrictions are lifted. However, a study, conducted in New York City, observed the travel behaviors of older adults (60 years and older) affected by COVID-19, according to the results, increased bike use among older adults during the pandemic was not as significant as among younger individuals, suggesting that there may be transportation barriers that older individuals must overcome in order to adopt micromobility (Gao, Lee, Ozbay, Zuo, & Chippendale, 2023).

In terms of distance usage, studies show that during the pandemic, people used micromobility services for longer and more distanced trips than prior to the pandemic (Abdullah, Dias, Muley, & Shahin, 2020; Li et al., 2020). Another study in Austin, Texas, showed that low-income areas with high availability of e-scooters experienced fewer declines in e-scooter trips, distance, and duration during the pandemic (Tuli, Nithila, & Mitra, 2023).

These previous studies have suggested that there is a need to improve infrastructure to support micromobility, as the pandemic may lead to permanent changes in travel behavior, particularly away from public transport (Lock, 2020). For example, a recent study in Metro Manila, Philippines, stated that the COVID-19 pandemic caused an increased awareness of environmental issues and the negative impacts associated with cars, leading to a permanent shift in attitude towards the use of e-scooters and electric bicycles (Gaspar, Prasetyo, Marinas, Persada, & Nadlifatin, 2023). It has also been suggested by a recent study in Oregon that the perceived health threat associated with COVID is likely to have a lasting impact on future transportation choices; due to the fact that people began to realize the feasibility and benefits of using other transportation options to reach destinations, e.g. parks by walking or bicycling (Y. Yang & Lewis, 2023). Additionally, a study reported that remote workers relocated from offices to car-centric suburban neighborhoods after the pandemic (Tan, Fang, & Lester, 2023). As such, it is important to understand COVID-19's impacts on people's decisions and preferences regarding these emerging modes of transportation.

2.9 Interactions of Micromobility with Other Road Users

Micromobility users often interact with many other road users. Although not necessarily considered a micromobility user, pedestrians share similar vulnerabilities as micromobility users when navigating complex transport networks. Addressing safety concerns for micromobility users may also have positive impacts on pedestrians as well.

These vulnerable road users (VRUs), including both micromobility users and pedestrians, represent a critical focus in global road safety discussions, accounting for nearly half of all traffic-related deaths ((WHO), 2023). In the United States alone, (NHTSA) (2023) reported approximately 7,388 pedestrian fatalities and 60,577 injuries in 2021, underlining the urgent need for improved interactions between drivers and VRUs. This improvement is essential for not only enhancing urban mobility but also ensuring the safety of all road users.

The relationship between drivers and VRUs is influenced by a complex array of factors, including but not limited to environmental conditions, infrastructure design, traffic characteristics, and individual driver characteristics. Craig, Morris, Van Houten, and Mayou (2019) found that the presence of pedestrian facilities, lane width, and behavior of other road users significantly influence drivers' perceptions of safety and their interactions with pedestrians. Others have identified that infrastructure such as dedicated bike lanes and pedestrian crossings promote safer driving practices and facilitate more positive interaction (Ojstersek & Topolsek, 2019; Fricker & Zhang, 2019; S, 2020; Luo, Liu, Mei, Chen, & Bi, 2023). Overall highlighting the significance of infrastructure in affecting interactions between pedestrians and vehicles.

Traffic characteristics, including flow and congestion, fundamentally shape how drivers perceive risks and respond on the road. High traffic volumes frequently lead to more aggressive driving, posing risks to the safety of pedestrians and cyclists (Li et al., 2020). Additionally, the variability in traffic flow during different times of the day can influence driver behavior towards VRUs. For instance, during peak traffic hours, drivers may experience increased stress and impatience, which can lead to riskier driving decisions such as speeding or neglecting to yield the right of way to pedestrians and cyclists (Morris & Hirsch, 2016).

Research into the dynamics of driver-pedestrian interactions at crossings has identified multiple factors that influence these encounters. Sucha, Dostal, and Risser (2017) demonstrated how variables such as vehicle speed, distance from a crossing, traffic density, and interpersonal cues from drivers (e.g., eye contact or gestures) significantly affect pedestrians' decisions to wait or proceed at marked crossings. These behaviors suggest that both environmental conditions and subtle driver communications play roles in pedestrian safety and decision-making processes. Additionally, Schneider, Wiers, and Schmitz (2022) found that both drivers' perceptions of pedestrian characteristics (e.g., age, mobility, perceived intent) and intrinsic driver characteristics (e.g., driving style and risk tolerance) also impact crossing safety. Goddard, Kahn, and Adkins (2015) highlighted the influence of deeper psychological and social identity-related factors, including racial bias, on drivers' yielding behaviors. This research underscores the importance of considering a broad spectrum of psychological, behavioral, and social factors in understanding and improving interactions at pedestrian crossings, pointing towards the need for comprehensive strategies that address both human and traffic-related elements to enhance road safety.

2.9.1 Personality Traits and Social Factors' Influence on Driver-VRU Interactions

Beyond these external influences, drivers' personality traits and emotional states can impact their decision-making processes and behaviors towards pedestrians, cyclists, and e-scooter users. Personality traits, as outlined in psychological frameworks like the Big Five, can dictate how drivers react in traffic situations. For instance, traits such as agreeableness and conscientiousness are often associated with more cautious and rule-following driving behaviors (Jackson et al., 2010). Drivers high in agreeableness are likely to be more considerate and patient towards VRUs, while those high in conscientiousness may demonstrate careful and vigilant driving habits (Jackson et al., 2010; Mongrain, Barnes, Barnhart, & Zalan, 2018). In contrast, traits like neuroticism and extraversion can lead to more erratic or aggressive driving. Drivers with high levels of neuroticism may overreact to stressful driving conditions, and those who are highly extroverted may engage in risky driving behaviors due to their tendency for seeking excitement and stimulation (Fetterman, Robinson, Ode, & Gordon, 2010; Thørrisen, 2013).

Emotional states also play a crucial role in influencing driver behavior. Research has shown that emotions such as anger or frustration can lead to impulsive and dangerous driving decisions. For example, drivers who are frustrated by traffic congestion or personal issues may exhibit less patience, which can manifest as speeding, abrupt lane changes, or failing to yield to VRUs (Eboli, Mazzulla, & Pungillo, 2017). Similarly, stress can impair cognitive functions, reducing a driver's ability to make quick and safe decisions, which is essential for reacting appropriately to the dynamic movements of pedestrians and cyclists (Sänger, Bechtold, Schoofs, Blaszkewicz, & Wascher, 2014). Furthermore, positive emotional states can also impact driving behaviors. Drivers who are in a good mood may be more attentive and courteous to VRUs, showing greater willingness to share the road and follow traffic rules conscientiously (Aknin, Van de Vondervoort, & Hamlin, 2018).

The influence of drivers' personality and emotions on their interactions with micromobility users and pedestrians presents a multifaceted challenge that necessitates an integrated understanding of individual behaviors, environmental contexts, and situational variables. This dissertation also seeks to extend the existing body of research by focusing on the roles of driver risk-taking tendency and emotional intelligence for micromobility integration.

2.10 Research Gaps

Despite the popularity of shared micromobility, the public has expressed concerns about aggressive riding behaviors, safety issues, and the abuse of street space. Gössling (2020) performed a content analysis on 173 media reports from 10 major cities and found that the top 3 frustrations experienced due to shared micromobility devices in many cities were irresponsible riding, safety/injuries, and e-scooter/bicycle clutter. Further literature is still needed to understand the disconnect between proponents and opponents of shared micromobility, which could identify opportunities to expand ridership to more diverse users. Previous literature has predominantly focused on the user-based perception on shared micromobility (Ruhrort, 2020). However, there is an increasing need to better understand the decision process of both users and non-users, and how certain factors can either deter or encourage shared micromobility adoption.

Overall, there has been a limited number of studies conducted since the launch of fourth-generation micromobility services. It is not yet clear how e-scooter and bicycle sharing services will change the way people travel in the future (James et al., 2019). Further, with travel behavior strongly influenced by the COVID-19 pandemic, it is important to understand potential shifts, trip replacement, and opportunities with micromobility mode choice.

Additionally, these shared micromobility users interact with and operate around motorized vehicles. This is especially true in areas with poorly dedicated infrastructure for bicycles and e-scooters. Hence, it is important to understand the factors that influence vehicle drivers' interactions with micromobility users, as vehicle interactions with these vulnerable road users have significant impacts to their safety, adoption, and long-term acceptance.

This dissertation takes a systematic approach to address these key research gaps in micromobility adoption, perception, and implementation. It first focuses on e-scooter users versus non-users (Chapter 4, RQ1), then investigates impacts from the COVID-19 pandemic on bicycles and e-scooters (Chapter 5, RQ2), and then evaluates vehicle-bicycle-pedestrian interactions (Chapter 6, RQ3).

Chapter 3

Methodology Overview

This dissertation leverages a variety of data sources and experimental designs. Each research question used a different dataset. A detailed description of the data and analytical methods for each research question is provided in the respective chapter presenting its results. However, an overview of the data used in each research question is provided in Table 3.1.

Table 3.1: Data used for each research question.

RQ	**Data Source**	**Sample Size**
1	Survey #1	409
2	Survey #2	134
	E-Scooter Trips	2,604
3	Survey #3	40
	Driving Simulator	40

The survey studies and driving simulator study each involved data collection with human subjects. Each study received approval from the Colorado State University Institutional Review Board (IRB). This ensured that ethical standards were followed and the rights and well-being of the participants were protected. Informed consent was obtained from each participant prior to beginning data collection.

In addition to including different datasets, micromobility was assessed from various system-level perspectives. Research questions 1 and 2 focused on micromobility user-specific influences on perceptions, preferences, and uses. Whereas research question 3 focused on interactions of drivers and micromobility users, with an emphasis on impacts to safety, such as speed, distance, and yielding behaviors.

These experimental designs and methods are further discussed in Chapters 4 through 6.

Chapter 4

RQ1: E-Scooter Users vs Non-Users

4.1 Introduction

Shared electric scooters (e-scooters) offer a potential strategy to mitigate environmental concerns and reduce congestion. However, successfully addressing these issues with e-scooters requires adoption across a diverse array of consumers. Moreover, equity should be considered when implementing this shared micromobility option, as all individuals should have access to environmentally friendly transportation alternatives. As such, understanding the differences between users and non-users can improve shared e-scooter appeal, operation, and safety.

This chapter addresses Research Question 1: What are the differences between shared e-scooter users and non-users, and what factors influence their decisions to use or not use shared e-scooters? The objective of addressing this question is to compare shared e-scooter users and non-users in terms of their perceptions on safety, trip behaviors, other shared modes, risk propensity, and willingness to adopt technology. A survey was conducted involving 210 (51.3%) users and 199 (48.7%) non-users of shared e-scooters. Binary logistic regression was used to model binary outcome variables (e-scooter user vs. non-user). This method is appropriate for understanding how multiple predictor variables (e.g., demographics, risk propensity) influence the likelihood of being an e-scooter user. Logistic regression is well-suited for binary outcomes and allows for the interpretation of odds ratios, which provide meaningful insights into the factors driving micromobility adoption. Chi-squared tests were applied to evaluate associations between categorical variables, such as e-scooter usage and demographic factors. This non-parametric method is particularly useful in understanding the relationship between categorical data, as it tests the independence of variables, providing clarity on whether certain categorical variables (e.g. demographic characteristics) are significantly associated with e-scooter adoption.

The results of this chapter have been published in the *Journal of Sustainability* (Pourfalatoun, Ahmed, & Miller, 2023).

4.2 Methods

A survey study was developed and administered to compare shared e-scooter users and non-users.

4.2.1 Design and Procedure

The survey was administered online using the Qualtrics survey software, which is a reliable and widely used tool for online data collection. This method was chosen for its convenience, accessibility and its ability to reach a broad audience for recruitment. Survey responses were gathered over a two-month period from December 2022 through to January 2023. The survey took, on average, 9.5 min to complete. The data was collected using a paid survey panel recruited through Qualtrics. Residents of the US state of Colorado were recruited with a target sample size of 400 complete responses. A stratified quota sampling method was employed, targeting approximately 200 shared e-scooter users and 200 non-users, to provide comparable groups for analysis.

The survey focused predominantly on shared e-scooters, rather than other shared modes or personal e-scooter ownership. It employed previously validated instruments to ensure the reliability and validity of the data (Buehler et al., 2021; Almannaa et al., 2021). Specifically, the survey consisted of questions related to participant demographics, typical commuting behaviors, frequency using various transportation modes, perceived safety concerns and usefulness of shared e-scooters, and compared the perceptions on shared e-scooters versus shared electric bicycles. These methods have been used and validated in previous studies, supporting the reliability and validity of our data. Furthermore, our survey incorporated the General Risk Propensity Scale (GRiPS) (D. C. Zhang et al., 2019) and assessed participants' technology adopter category, as characterized by Rogers' (R. L. Miller, 2015) five classifications for the diffusion of innovations. Both the GRiPS and

Rogers' categories have been shown to be valid and consistent in previous studies, thus lending credibility to our results in the context of e-scooter use. By using such validated instruments, we aimed to ensure the rigor of our study and the robustness of the findings. A copy of this survey is provided in Appendix A.

4.2.2 Survey Participants

A minimum age of 18 years old was required for all participants, and all participants had to reside within the state of Colorado. Participants who had never used a shared e-scooter were grouped as non-users, and those who reported using a shared e-scooter at least monthly were grouped as users. The survey received a total of 409 responses from 210 (51.3%) users and 199 (48.7%) non-users. The average age of the participants was 39.6 years old (SD = 16.3). The sample consisted of 11 (2.7%) participants with less than a high school degree, 227 (55.5%) with a high school diploma, 106 (25.9%) with a bachelor's degree, 58; (142%) with a post-graduate degree as their highest level of education completed, and 7 (1.7%) preferred not to answer. Additionally, we had 266 (65.0%) White, 64 (15.6%) Hispanic or Latino, 36 (8.8%) Black or African American, 18 (4.4%) two or more races, 10 (2.4%) Asian or Pacific Islander, 6 (1.5%) Native American, and 9 (2.2%) other participants. There were 181 (44.3%) participants with a household income of less than USD 50k, 132 (32.3%) with between USD 50k to USD 100k, 95 (23.2%) with greater than USD 100k, and 1 (0.2%) preferred not to answer. A further overview of the respondent demographics is provided in Table 4.1.

While the survey population was not entirely representative of the general population in Colorado, it was appropriate for our research objective, which was to investigate the differences between e-scooter users and non-users. When compared to US census data, for example the proportion of females in the sample was higher than the general population in Colorado (71.6% vs. 49.3%). While the proportion of participants from rural areas in the sample was closer to that in the general Colorado population (15.7% vs. 13%). Similarly, 59.2% of our sample was employed, compared to 67.8% of the Colorado population age 16 and over in the civilian labor force. The

Table 4.1: Participant demographics by shared e-scooter user groups.

Demographic	User (N = 210) *N (%)*	Non-User (N = 199) *N (%)*	All (N = 409) *N (%)*
Gender			
Male	62 (31.1%)	50 (23.8%)	112 (27.4%)
Female	135 (67.8%)	158 (75.2%)	293 (71.6%)
Other	2 (1.0%)	2 (0.9%)	4 (1.0%)
Age			
18–24	53 (26.6%)	35 (17.1%)	88 (21.8%)
25–34	68 (34.1%)	34 (16.6%)	102 (25.25%)
35–44	49 (24.6%)	34 (16.6%)	83 (20.54%)
45–54	21 (10.6%)	33 (16.1%)	54 (13.37%)
55–64	5 (2.5%)	34 (16.6%)	39 (9.7%)
65 and over	3 (1.5%)	35 (17.1%)	38 (9.4%)
Employment Status			
Student	32 (16.1%)	22 (10.5%)	54 (13.2%)
Employed	133 (66.8%)	109 (51.9%)	242 (59.2%)
Not Employed	34 (17.1%)	79 (37.6%)	113 (27.6%)
Residential Location			
Rural	25 (12.6%)	39 (18.7%)	64 (15.7%)
Suburban	92 (46.5%)	120 (57.4%)	212 (52.1%)
Urban	81 (41.0%)	50 (24.0%)	132 (32.3%)

state of Colorado was 67% White, compared to our 65%. Lastly, the proportion of our sample with a bachelor's degree or higher was 40.1%, compared to 42.8% for the state of Colorado.

4.2.3 Data Analysis

Data cleaning and analysis were conducted using Python (version 3.6.12), SPSS (version 28.0.0.0) and Tableau (version 2022.4). Initial data cleaning was conducted by Qualtrics for quality control, where incomplete responses were removed and responses completed in one-half of the median completion time were removed, which resulted in 409 complete responses used in the analysis. Statistical significance was evaluated at $\alpha = 0.05$. Binary logistic regression, chi-squared tests, Cochran's Q tests and McNemar tests were performed to compare users and non-users of shared e-scooters.

Dependent Variable - User vs Non-User

The dependent variable used in the analysis was shared e-scooter group membership, which was a binary variable coded as shared e-scooter user or non-user. A shared e-scooter user was a familiar user, defined as someone that reported using a shared e-scooter at least monthly. A shared e-scooter non-user was defined as someone that reported never having ridden one.

4.3 Results

4.3.1 Demographics by User Group

Basic demographic profiles of shared e-scooter users and non-users from our respondents were compared to gain insights about characteristic differences between user groups. A binary logistic regression model was used with the dependent variable shared e-scooter user (1) and non-user (0), see Table 4.2. Hence the model predicts likelihood of being a user, where variables with a positive coefficient value increase the likelihood of being a user. Based on these results, shared e-scooter users are significantly younger (negative coefficient for increasing age variable), are employed (i.e., not students), live in urban areas, and have commutes longer than 1 mile.

Table 4.2: Logistic regression predicting users based on demographics.

Variable	**Coeff.**	**Std Error**	**z-score**	**p-value**
(Intercept)	0.027	0.673	0.040	–
Age	-0.059	0.009	-6.513	$< .001$
Female *(ref: male)*	-0.305	0.257	-1.188	ns
Employed *(ref: student)*	1.067	0.486	2.193	0.028
Not Employed *(ref: student)*	0.866	0.547	1.582	ns
Suburban Residential *(ref: rural)*	0.253	0.333	0.760	ns
Urban Residential *(ref: rural)*	1.098	0.363	3.022	0.003
Commute 1-5 miles *(ref: <1 mile)*	1.144	0.387	2.957	0.003
Commute 6-10 miles *(ref: <1 mile)*	1.181	0.397	2.975	0.003
Commute >10 miles *(ref: <1 mile)*	1.124	0.418	2.688	0.007

Note: Nagelkerke R2 = 0.301

4.3.2 Risk Propensity and Technology Adoption in Predicting User Groups

The general risk propensity scale, GRiPS (D. C. Zhang et al., 2019) was used to measure risk-taking behaviour. GRiPS uses eight questions to measure general risk propensity on a scale of 1 (strongly disagree) to 5 (strongly agree), where a higher average score equates to being more of a risk taker. The range of responses and average response for each question by user group is shown in Figure 4.1. For all eight questions, the average score is lower for shared e-scooter non-users than users. Moreover, the overall average score across all eight questions reveals a significant difference between the two groups, where shared e-scooter users have a higher mean risk score (M = 3.29, SD = 0.87) compared to non-users (M = 2.61, SD = 1.03): $t(400.11) = 7.285$, $p < .001$.

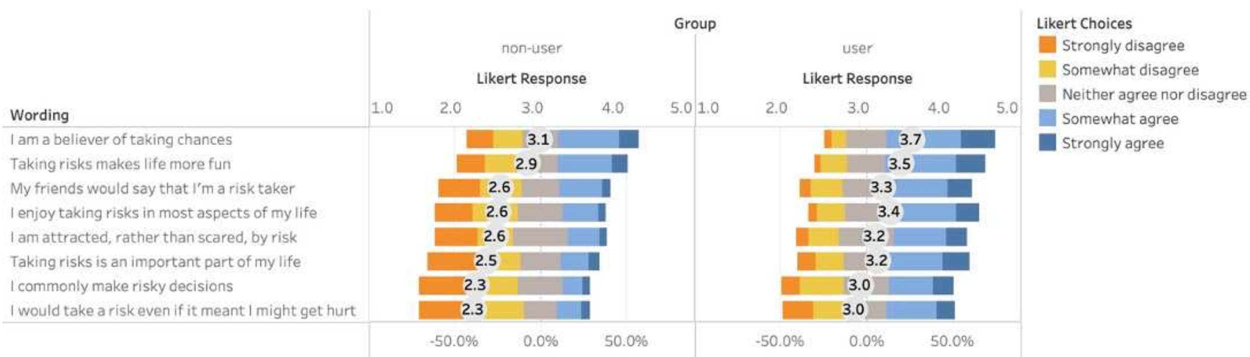

Figure 4.1: Comparison of responses for each risk propensity question by user group, where average scores are denoted in each circle.

Participants were asked about their general affinity to adopt new technologies, which aligned with Rogers' (R. L. Miller, 2015) five classifications for diffusion of innovations. We used their response to define their technology adoption profile as either: innovator, early, early majority, late majority, or laggard, see Figure 4.2. There are noticeably more 'innovators' and less 'laggards' in the user group as compared to the non-user group.

Next, binary logistic regression was conducted to predict user group membership based on risk propensity and technology adoption profiles. Age was also included in this model because it tends to be associated with risk propensity and user group. The model is summarized in Table 4.3. The regression results indicate that both technology adoption and risk propensity significantly predict

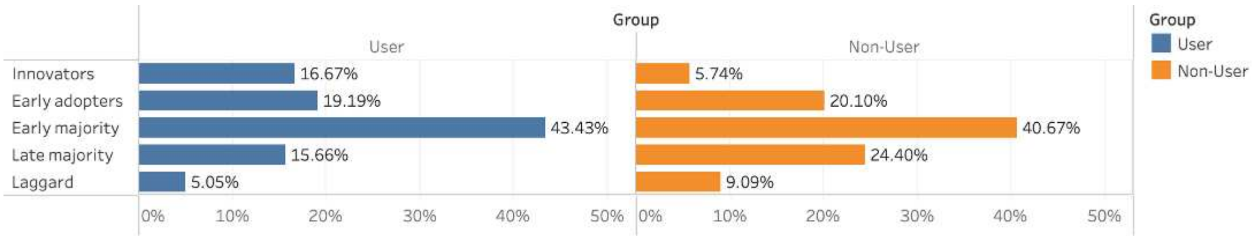

Figure 4.2: Comparison of technology adoption profiles by user group.

shared e-scooter usage. Specifically, each one unit increase in average risk score increases the odds of being a shared e-scooter user by 0.423. Shared e-scooter users are also more likely to be early majority or innovators in terms of technology adoption profiles.

Table 4.3: Logistic regression predicting users based on risk and technology profiles.

Variable	Coeff.	Std Error	z-score	p-value
(Intercept)	-0.322	0.697	-0.462	–
Average Risk Score	0.423	0.130	3.259	0.001
Technology Adopter Profile (ref: Laggard)				
Late Majority	0.520	0.496	1.050	ns
Early Majority	0.912	0.458	1.989	0.047
Early Adopter	0.573	0.488	1.175	ns
Innovator	1.563	0.563	2.778	0.005
Age	-0.045	0.008	-5.472	$< .001$

Note: Nagelkerke R2 = 0.265

4.3.3 Perceptions Relating to Safety

Helmet Use

Participants were asked to what extent they thought helmets were necessary while riding shared e-scooters. There was a significant relationship between user group and perceived importance of wearing a helmet: $\chi 2$ (4, N = 409) = 19.61, p = .001. Specifically, non-users are more likely to consider a helmet extremely necessary while riding a shared e-scooter. Whereas there was no strong opinion about whether helmets are necessary among users, see Figure 4.3.

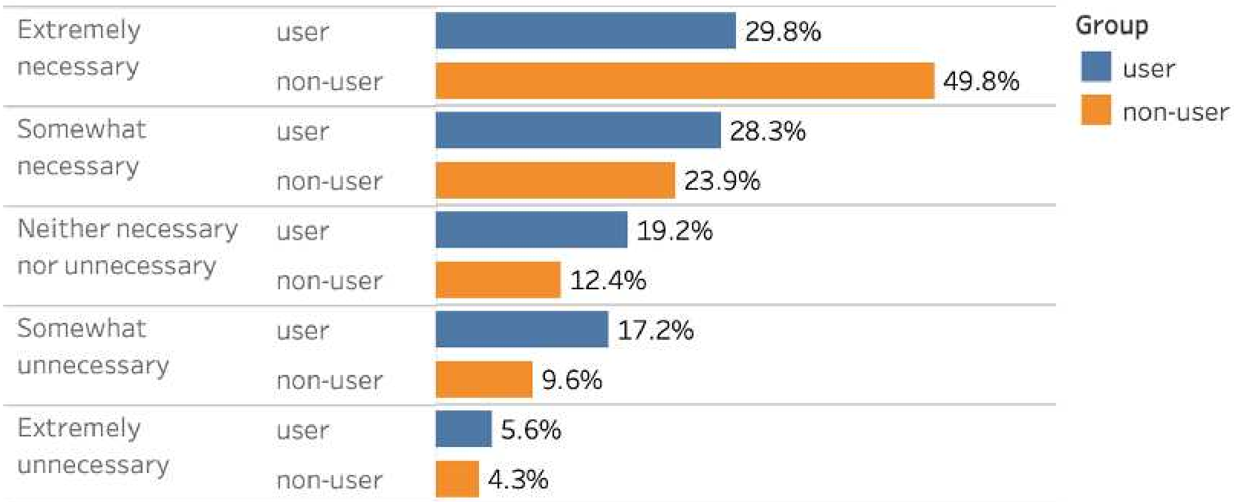

Figure 4.3: Perceptions on the importance of helmets while riding a shared e-scooter.

Speed and Riding Scenarios

Additionally, participants were asked whether they feel safe or unsafe regarding the speed of shared e-scooters and different hypothetical riding scenarios, see Figure 4.4. Chi-squared tests were performed to compare users versus non-users regarding each scenario. The results indicate that there is a significant difference between users and non-users in their safety perceptions of shared e-scooters, where users consider it safe to ride shared e-scooters on the sidewalk ($\chi2$ (1, N = 409) = 34.63, $p < .001$), to get passed by a rider as a pedestrian on the sidewalk ($\chi2$ (1, N = 409) = 24.45, $p < .001$), to ride in the vehicle lane ($\chi2$ (1, N = 409) = 17.28, $p < .001$), and they also feel safe regarding the speed of the device ($\chi2$ (1, N = 409) = 27.66, $p < .001$). On the other hand, non-users consider these as unsafe.

Infrastructure Needs

Participants were asked what changes in infrastructure would increase their perception of safety on or around shared e-scooters. This question allowed respondents to select multiple options, see Table 4.4. According to Cochran's Q test, the choices made by the two groups differed significantly: $\chi2$ (5, N = 409) = 179.16, $p < .001$. Based on chi-squared tests as a post hoc test, non-users are more likely to feel safer if separated bike lanes with a physical barrier existed ($p = .03$). No

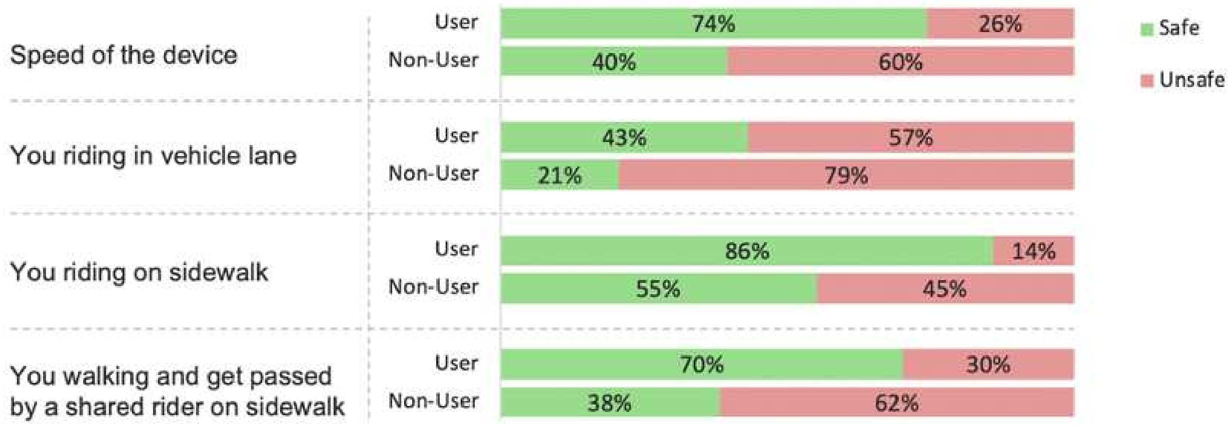

Figure 4.4: Comparing safety perceptions regarding speed and riding scenarios by user group.

other significant difference was observed between the other infrastructure options. Both users and non-users tended to agree that smoother pavement is important and that no ride zones are least important.

Table 4.4: Preferences of infrastructure changes to enhance safety.

Infrastructure Improvement	**User (N=210)** *N (%)*	**Non-User (N=199)** *N (%)*
Smoother Pavement	114 (54.3%)	102 (51.3%)
Wider Bike Lanes	97 (46.2%)	98 (49.2%)
Separated Bike Lanes with Physical Barrier	91 (43.3%)	117 (58.8%)
Designated E-Scooter Parking	70 (33.3%)	63 (31.7%)
Wider Sidewalks	64 (30.5%)	63 (31.7%)
No Ride Zones for E-Scooters	31 (14.8%)	47 (23.6%)

4.3.4 Differences in Perceptions of Shared E-Scooters vs Shared E-Bikes

A common question amongst academics and practitioners is whether shared e-scooters are serving a different population from shared bicycles. We compared various perceptions of these two modes between shared e-scooter users and non-users, see Figure 4.5. Chi-squared tests were performed to compare users versus non-users within a mode, e.g., comparing opinion about 'feeling safe riding a shared e-scooter' between users and non-users, and about 'feeling safe riding a shared e-bicycle' between users and non-users, etc. McNemar tests were used to compare within user groups across modes, e.g., comparing opinion about 'feeling safe riding a shared e-bicycle' versus 'feeling safe riding a shared e-scooter' for users, and again for non-users, etc. Hence, chi-squared tests yielded differences in perceptions between user groups, while McNemar tests yielded differences in perceptions between transportation modes. McNemar tests were used because the data was paired, as there was an observation for the same participant regarding their perception of shared e-scooters and shared e-bicycles. The results of these tests are shown in Figure 4.5, where * denotes $p < .05$, ** for $p < .01$, and *** for $p < .001$.

Figure 4.5: Differences in perceptions of shared e-scooters and shared e-bicycles based on user group, where lines connecting bars denote a significant pairwise comparison.

The chi-squared results indicate that there is a significant difference between users and non-users in their perceptions of shared e-scooters, where users have overall more positive perceptions of safety ($\chi 2$ (2, N = 409) = 32.69, $p < .001$), sanitary level ($\chi 2$ (2, N = 409) = 17.31, $p < .001$), comfort riding intoxicated ($\chi 2$ (2, N = 409) = 14.60, $p < .001$), and usability ($\chi 2$ (2, N = 409) = 51.55, $p < .001$) of shared e-scooters, as compared to non-users. These trends were similar in their perceptions of shared e-bicycles, however there was no difference in user versus non-user perceptions of sanitary levels of shared e-bicycles; safety ($\chi2$ (2, N = 409) = 22.18, p < .001), sanitary level ($\chi2$ (2, N = 409) = 2.03, p = ns), comfort riding intoxicated ($\chi2$ (2, N = 409) = 6.95, p = .03), and usability ($\chi2$ (2, N = 409) = 20.93, p < .001) of shared e-bicycles. McNemar's tests showed that there were no differences in perceptions of shared e-bicycles versus shared e-scooters for non-users. However, users are more positive to-wards the sanitary levels of e-scooters over e-bicycles ($\chi2$ (3, N = 409) = 8.21, p = .04), and about the usability of e-scooters over e-bicycles ($\chi2$ (3, N = 409) = 11.27, p = .01). Meanwhile, there were no differences in users' perceptions of safety or riding intoxicated between shared e-scooters and shared e-bicycles.

4.3.5 Trip Purposes for Shared E-Scooters

Another binary logistic regression was conducted to predict the likelihood of being a shared e-scooter user or non-user based on shared e-scooter use for various trip purposes: commuting to work/school, commuting to remote parking areas, for leisure/fun, for personal tasks (e.g., grocery, bank), and for exploring a new city. Shared e-scooter users were asked how frequently they use shared e-scooters for these various trips and non-users were asked how frequently they would consider using shared e-scooters for the various trips. For each trip purpose, responses were coded as 'rarely/never' or 'at least once a month.' The analysis revealed significant associations between shared e-scooter use for specific purposes and the likelihood of being a shared e-scooter user, see Table 4.5.

The intent to use a shared e-scooter for commuting to work/school significantly predicts being a user (Odds Ratio = 2.79). Similarly, those who intend to use shared e-scooters for commuting to remote parking (Odds Ratio = 2.24) and for leisure/fun (Odds Ratio = 7.87) are also more likely users. However, shared e-scooter use for personal tasks and exploring a new city did not significantly predict the likelihood of being a user or non-user in this study (p > .05).

Table 4.5: Logistic regression predicting users based on trip purpose.

Variable	Coeff.	Std Error	z-score	p-value
(Intercept)	-2.807	0.349	-8.038	–
Commute to work/school	1.026	0.345	2.978	0.003
Commute to remote parking	0.807	0.334	2.415	0.016
For leisure/fun	2.063	0.472	4.373	$< .001$
For personal tasks (e.g., grocery)	0.428	0.335	1.280	ns
For exploring a new city	0.607	0.374	1.621	ns

Note: Nagelkerke R2 = 0.578

4.3.6 Motivations for Using Shared E-Scooters

Lastly, participants were also asked about the reasons that would motivate (non-users) or have motivated (users) them to use a shared e-scooter, which included: to save time, to save money, for parking convenience, for fun/adventure, or for environmental reasons. Participants were instructed to select all that applied, i.e., not limited to one selection. Responses were recorded for each group and analyzed to determine the most common motivations, see Table 4.6.

Table 4.6: Comparison of motivational factors among users and non-users.

Motivational Factor	User (N=210) *N (%)*	Non-User (N=199) *N (%)*
For Fun/Adventure	120 (57.1%)	128 (64.3%)
To Save Money	99 (47.1%)	61 (30.7%)
To Save Time	82 (39.0%)	49 (24.6%)
For Parking Convenience	80 (38.1%)	74 (37.2%)
For Environmental Reasons	50 (23.8%)	67 (33.7%)

Cochran's Q test showed a significant difference between the motivational factors chosen by the two groups: $\chi 2$ (4, N = 409) = 127.05, $p < .001$. Chi-squared tests were used as a post hoc test, which showed that e-scooter users are mostly motivated by "saving money" and "saving time" in comparison with non-users not being motivated by these factors ($p < .001$). In both user groups, "fun/adventure" was the most selected factor for wanting to use shared e-scooters.

4.4 Discussion

This chapter examined how shared e-scooter users and non-users perceive shared e-scooters differently in various situations regarding safety, trip behavior and in relation to other shared modes, as well as their risk-taking propensity and their acceptance of new technologies. Participants who had never used a shared e-scooter were categorized as non-users (N = 199) and those who reported using a shared electric scooter at least monthly were categorized as users (N = 210).

Perceptions on safety, particularly in relation to helmet usage, exhibited considerable variation between the user groups. Non-users, whose opinions might have been shaped by observations or anecdotal information rather than personal experience, deemed helmets to be of utmost importance. In contrast, users expressed more moderate views on helmet necessity. These findings are aligned with a recent study, which stated that users consider e-scooters safe, while non-users consider them as unsafe (della Mura et al., 2022). Contrary to non-users, users reported feeling safe regarding the speed and in a variety of e-scooter scenarios, including riding on sidewalks and walking and being passed by an e-scooter. Both cohorts, however, concurred that infrastructure improvements, including smoother pavements, dedicated bike lanes, and physical barriers, were essential for promoting safety. Notably, non-users emphasized the significance of physical barriers in fostering a secure environment for e-scooter riders. Similarly, Sievert, Roen, Craig, and Morris (2023) reported that protected bicycle lanes were perceived as the safest infrastructure for riding e-scooters, amongst 329 surveyed riders. While helmet usage was mostly a concern of non-users, infrastructure was a concern for both users and non-users, and public policy could be improved by emphasizing protected bicycle lanes, rather than helmet mandates, as a means of protecting all vulnerable road users from the dangers associated with e-scooters.

Overall, both users and non-users of e-scooters expressed feeling unsafe riding them in vehicle lanes. Considering that both groups reported feeling safe riding these modes on sidewalks, one explanation could be that car speeds and their presence in the same shared lane makes them less in control and more vulnerable, resulting in more serious injuries. These findings are supported by a recent case study that discussed injuries sustained by micromobility riders, concluding that micromobility riders are more vulnerable to severe injuries in crashes with vehicles, due to having to share transportation facilities with others and their inherent vulnerability compared to cars (Fang, 2022).

When comparing shared e-scooters and e-bikes, users generally had more positive perceptions of e-scooters, specifically in terms of their sanitation and usability. However, there were no significant differences in the perceptions on safety and riding while intoxicated between the two modes for the users. This finding suggests that shared e-scooters possess a unique appeal, but further research is necessary to explore the factors that influence user preferences and distinguish shared e-scooters from other transportation options.

Additionally, users in our study exhibited a higher propensity for risk taking and were more likely to be early technology adopters compared to non-users. Our binary logistic regression analysis demonstrated that both risk propensity and technology adoption profiles significantly predict shared e-scooter usage. These findings align with previous research on the psychology of early adopters and risk-taking behavior, suggesting that shared e-scooter users are more open to exploring innovative modes of transportation and may exhibit a greater tolerance for potential risks associated with their use (Kopplin, Brand, & Reichenberger, 2021). In contrast, non-users tend to exhibit more conservative attitudes, potentially avoiding shared e-scooters due to concerns about safety, unfamiliarity with the technology, or a preference for traditional transportation methods.

We also found that having fun was the primary motivator for both shared e-scooter users and non-users who would consider using a shared e-scooter. This indicates that the enjoyable experience of riding an e-scooter is a key factor in attracting people to the service. For users, saving money and saving time were the next most important factors, suggesting that these users appreciate the cost and time efficiency provided by shared e-scooters. These findings are consistent with a survey study in Tampa, Florida regarding factors influencing shared e-scooter usage, in which fun, getting around faster and saving money were reported to be among the top three motivating factors (Guo & Zhang, 2021). In contrast, non-users placed greater importance on commuting to parking lots and preserving the environment, indicating that they might be more likely to adopt shared e-scooters if these aspects were emphasized or improved. Similarly, Eccarius and Lu (2018) reported that the top motivations for e-scooter usage in Taiwan were environmental concerns and convenience.

The logistic regression model based on demographics revealed that younger, employed individuals with commutes longer than 1 mile and living in urban areas were more likely to be shared e-scooter users. These findings strongly align with existing literature on the demographic characteristics of shared e-scooter users (Pazzini et al., 2022). Younger individuals tend to be more tech savvy and comfortable with adopting new technologies. The use of shared e-scooters often requires smartphone applications and familiarity with digital interfaces, which may be more accessible to younger users. Similarly, urban areas typically have better developed infrastructure to support e-scooters, such as dedicated bike lanes and accessible charging stations, which may encourage their use among urban residents. Moreover, shared e-scooters can be more cost effective than owning a personal vehicle or relying on public transportation, particularly in urban areas where parking fees and traffic congestion can be significant deterrents.

These distinctions between user groups highlight the importance of tailoring communication and outreach strategies to address the differing concerns and preferences of these distinct demographics. For instance, targeted marketing campaigns and educational initiatives for non-users could focus on addressing safety concerns, providing clear instructions for proper e-scooter use and emphasizing the benefits of e-scooters as an alternative to traditional transportation options. Such efforts may help mitigate apprehension and encourage broader adoption of shared e-scooters.

Moreover, understanding the psychological factors that influence shared e-scooter adoption can inform the design and implementation of policies and infrastructure that cater to the needs of both user groups. For example, policymakers could consider implementing measures to enhance safety, such as designated e-scooter parking zones and speed limits, to address the concerns of more risk-averse individuals. By acknowledging and accommodating the distinct perspectives of users and non-users, city planners and e-scooter companies can develop strategies that foster a more inclusive and sustainable urban transportation ecosystem.

It is relevant to note that a potential limitation of this work is our groupings of users/non-users based on using an e-scooter at least monthly versus never having ridden one. Future research, with a larger sample size, could group users/non-users into more granular groups based on ridership frequency, such as weekly versus a few times per year versus never. As this differentiation and motivation for using or not using e-scooters at these levels could provide further insights into different user types.

4.5 Conclusions

This chapter contributes to the growing body of literature on shared e-scooter adoption by examining the differences in demographics, trip purposes, motivations, safety perceptions, risk-taking behaviors and technology adoption profiles between users and non-users. Non-users, likely influenced by observations and anecdotal information, placed more emphasis on helmet usage, whereas users were more moderate in their helmet necessity views. Infrastructure improvements were deemed necessary by both groups for enhancing safety. Interestingly, users exhibited a higher propensity for risk taking and were more likely to be early technology adopters. Fun was identified as the primary motivator for both groups, with users also valuing cost and time efficiency, and non-users expressing interest in the environmental benefits. Our logistic regression model indicated that younger, employed individuals living in urban areas with longer commutes were more likely to be users. The findings provide a more nuanced understanding of the factors that influence shared e-scooter adoption and have implications for operators, policymakers and researchers.

For operators, understanding the demographics, motivations and trip purposes of shared e-scooter users can inform targeted marketing campaigns and service offerings. For example, operators could emphasize the time and cost-saving benefits of e-scooters to attract potential users, while focusing on providing services for work/school commutes and leisure activities. Additionally, operators should consider implementing safety features and educational programs to address concerns related to helmet use and risk-taking behaviors.

Policymakers should recognize the importance of infrastructure improvements, such as smoother pavements, separated bike lanes and physical barriers, in promoting shared e-scooter adoption and ensuring rider safety. By investing in safer and more accessible infrastructure for e-scooters and other micromobility options, policymakers can encourage the use of these sustainable modes of transportation and help reduce congestion, pollution and the dependence on personal vehicles in urban areas.

Researchers should continue to explore the factors influencing shared e-scooter adoption, including barriers to use among non-users and the role of social norms and peer groups. Longitudinal studies with more diverse and representative samples will help to establish causal relationships between variables and provide a more comprehensive understanding of shared e-scooter adoption patterns. Moreover, comparative studies between shared e-scooters and other micromobility options can offer insights into the unique appeal of each mode of transport and inform strategies for promoting their use.

Chapter 5

RQ2: COVID-19 Impacts

5.1 Introduction

Travel behavior was and continues to be affected by the COVID-19 pandemic. Shared micromobility are likely more vulnerable to these changes, as a relatively new mode, with less habitual riders and their shared nature perceived as a higher risk. As such, understanding how use and behavior with these devices may have changed is important for adjusting implementation and outreach strategies.

This chapter addresses Research Question 2: How did preferences and perceptions of micromobility change before, during, and after the pandemic, and in relation to quarantine behaviors? Shared electric scooter trip data (N = 2,604) before and during the pandemic, and survey data (N = 134) during the pandemic, were collected and analyzed to explore this topic.

The results of this chapter have been published in the *Journal of Transportation Research Interdisciplinary Perspectives* (Pourfalatoun & Miller, 2023). Additionally, this work was presented at a poster session at the *Applied Human Factors and Ergonomics Society International Conference* (Pourfalatoun & Miller, 2022).

5.2 Methods

This study analyzed shared e-scooter trip data and survey responses from both e-scooter users and non-users.

5.2.1 Survey Data

The survey was developed and administered online using the Qualtrics Survey Software. The survey was administered in Fort Collins, Colorado from May through June 2021 and took approximately 15 min to complete. During the data collection period for this study, Fort Collins only allowed operation from one scooter share company. This scooter company collaborated with the researchers of this project to recruit survey participants. Specifically, individuals that had rented an e-scooter at least once in Fort Collins over the previous six months from survey deployment were emailed the survey from the scooter share company. Additional respondents were also recruited within Fort Collins to capture perceptions of non-scooter users as well. These participants were recruited through flyers and emails.

As part of the survey, participants were asked to describe their quarantine behavior during the COVID-19 pandemic; this was used to group participants into different quarantine behavior groups. Participants were asked about their transportation mode use before and during the pandemic, as well as their intentions of mode choice after the pandemic. The survey also captured general perceptions about shared e-scooters and shared bicycles. A copy of this survey is provided in Appendix B.

5.2.2 Survey Participants

A total of 134 participants completed the survey; 47.0% were male, 32.1% were female, and 20.9% preferred not to answer. Sixty-one (45.5%) of the respondents reported having ridden a shared e-scooter at least once. Participants were not required to answer every question if they did not want to, hence, in some questions, the total number of respondents is lower than the total number of participants in the survey. However, all 134 participants included in this analysis completed at least three-quarters of the survey and answered the quality control question correctly, which served as data cleaning.

5.2.3 Determination of Survey Sample Size

The anticipated sample size was determined using Equation 5.1, based on a preferred 95% confidence level (Z = 1.96) with a margin of error of 10% (e = 0.1). Since the sample proportion (p) was unknown, a value of 50% was used (p = 0.5), which provides the most conservative estimate for sample size. Since the population of Fort Collins was about 170,000 (N), the desired sample size was determined to be 96 respondents. As such, our sample size of 134 survey respondents provides a slightly better than anticipated margin of error, of +/- 8.4%.

$$Sample\ Size = \frac{\frac{z^2 \times p(1-p)}{e^2}}{1 + \frac{z^2 \times p(1-p)}{e^2 N}} \tag{5.1}$$

5.2.4 E-Scooter Trip Data

As part of the agreement between the scooter company that provided the data and the research team, the exact company cannot be revealed. The scooteres operated by this company had a maximum operating range of 25 miles and maximum speed of 18 mph. The e-scooters were rented and paid for by users through the company's phone app.

To explore the impact of the COVID-19 pandemic on the usage and perception of micromobility, data from two weeks of trips were examined: one week prior to the pandemic (January 25-31, 2020) and one week during the pandemic (January 25-31, 2021). There were 2,152 scooter trips for the pre-pandemic week and 560 scooter trips for the during-pandemic week. The two weeks selected for data analysis were carefully selected. First, the scooter share had only been introduced in October 2019, a few months prior to the onset of the pandemic, limiting the options prior to the pandemic. The scooters were removed from the city from March 2020 through June 2020, during the onset of the pandemic, so this period was not available. Additionally, since the study location is a mid-sized college town, we wanted to select a period during the semester when scooter use was likely high. Lastly, weather conditions were considered to provide the most comparable pre- and during-pandemic conditions, where ultimately the weeks selected did not have any precipitation.

The scooter trip data includes origin location (latitude/longitude) and timestamp, destination location (latitude/longitude) and timestamp, and trip route (latitude/longitude and timestamp) sampled between 2-4 Hz. The timestamps, which were measured to the millisecond, were used to calculate the duration of each trip.

5.2.5 Weather Data

As discussed above, we wanted to minimize the effects of weather on scooter trips between our pre-and during-pandemic weeks by selecting two weeks with comparable weather conditions. Weather data for Fort Collins during these two weeks was gathered from the AccuWeather website. As shown in Figure 5.1, the weather patterns between the two weeks were very similar; most notably, the temperatures and precipitation.

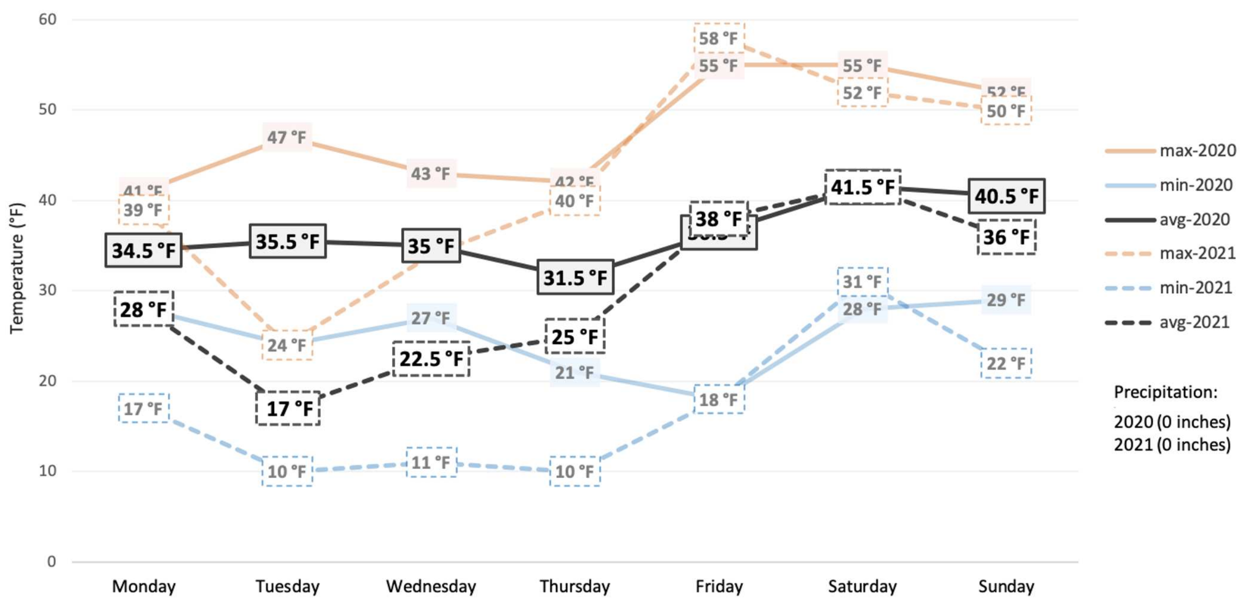

Figure 5.1: Weather data (temperature and precipitation) comparison for before and during pandemic weeks.

5.2.6 Data Analysis

Data cleaning and analysis were done using Python (version 3.6.12), R (version 4.1.2), and Microsoft Excel (version 16.60). Statistical significance was evaluated at $\alpha = 0.05$. Analysis of variance (ANOVA) was used to test for a difference in trip durations and trip counts before and during the pandemic. Tukey Honest Significant Difference (HSD) test was used to evaluate pairwise comparisons of the ANOVA. Fisher's exact tests were used to identify differences in travel behavior before and during the pandemic between the three quarantine behavior groups.

Chi-square tests were used to evaluate the overall differences in mode choice before, during, and after the pandemic.

5.3 Results

5.3.1 Quarantine Behavior Groups - Survey Data

The survey was conducted in May and June of 2021, about 14 months after the first official COVID-19 case in the state and county. Participants were asked to best describe their quarantine status over the previous six months and 100 of the 134 provided that information. None of the participants reported being in full isolation (i.e., not leaving their home at all) during this time span. Participants were grouped into three quarantine behavior groups based on their responses: Group 1 (27.0%) reported they left their house similar to before the pandemic; Group 2 (24.0%) reported they only left their house for essential activities; and Group 3 (49.0%) reported they left their house only for essential activities and for their work.

Quarantine Behavior Group Demographics

The breakdown of employment status, transportation mode ownership, and typical commute distance for each group is provided in Table 5.1. Across all groups, most of the respondents were full-time workers followed by students. Participants were asked to select all that applied in terms of transportation mode ownership, hence, the percentages for each category total more than 100%. In all groups, over half of the participants reported owning a bicycle and vehicle. However, a higher proportion of people owned vehicles in Groups 1 and 2 than any other mode, while a higher proportion of people owned bicycles than any other mode in Group 3. The most typical commute mileage of all three groups was 1-5 mile. Group 1, in comparison with the other groups, had the highest proportion of commuting more than 10 miles (25.9%).

Table 5.1: Demographics of participant quarantine behavior groups.

Demographic Variable	**Quarantine Behavior Group**		
	1: Left house similar to before pandemic	*2: Only left for essential activity*	*3: Only left for essential activity and work*
Total Respondents	27%	24%	49%
Employment Status			
Student	29.6%	33.3%	24.4%
Part-time	3.7%	4.1%	12.2%
Full-time	62.9%	62.5%	61.2%
Not employed	3.7%	0%	2%
Transportation Mode Ownership			
Vehicle	88.8%	70.8%	73.4%
Bicycle	66.6%	66.6%	77.5%
Scooter	7.4%	4.1%	2%
None	0%	8.3%	4%
Typical Commute Mileage			
< 1 mile	7.4%	16.6%	14.2%
1-5 miles	55.5%	50%	53%
6-10 miles	11.1%	20.8%	18.3%
> 10 miles	25.9%	8.3%	14.2%

5.3.2 Differences in Perceptions of Shared Modes by Quarantine Behavior Group - Survey Data

A comparison of experience riding shared e-scooters, shared bicycles, and perceived cleanliness of each shared mode by quarantine behavior group is provided in Table 5.2. A chi-square test indicated no relationship between quarantine behavior group and experience riding shared e-scooters, $\chi 2$ (4, N = 100) = 5.03, p =.285. Further, across all groups, participants reported having more experience riding shared e-scooters rather than shared bicycles. A chi-square test was also conducted to compare perceived sanitary levels of shared e-scooters by group, which also indicated no difference in perceived cleanliness based on quarantine group: $\chi 2$ (4, N = 100) = 2.20, p =.700. In fact, most participants did not have a strong opinion about the sanitary levels of both shared e-scooters and shared bicycles, with 'Neutral' being the most frequently chosen option.

Table 5.2: Differences in perceptions of shared scooters and shared bicycles by quarantine behavior group.

Variable	1: Left house similar to before pandemic		2: Only left for essential activity		3: Only left for ess. activity and work	
	Shared Scooter	*Shared Bicycle*	*Shared Scooter*	*Shared Bicycle*	*Shared Scooter*	*Shared Bicycle*
Riding Experience						
Ridden	51.8%	25.9%	45.8%	37.5%	61.2%	40.8%
Only seen	33.3%	44.4%	20.8%	29.1%	24.4%	28.5%
None	14.8%	29.6%	33.3%	33.3%	14.2%	30.6%
Perception of Sanitation						
Unsanitary	29.6%	18.5%	25%	16.6%	16.3%	22.4%
Neutral	44.4%	44.4%	50%	50%	44.8%	36.7%
Sanitary	22.2%	29.6%	25%	33.3%	26.5%	28.5%

Survey participants were also asked how likely they would be to use various shared modes (bicycle/e-scooter, public transit, Uber/Lyft) before and during the pandemic. Fisher's exact test was used to determine if there was a significant association within each quarantine behavior group in terms of transport mode choice before versus during, where statistical significance is denoted with a solid black line connecting the modes before/after the pandemic in Figure 5.2. For Group (1) (left house similar), there was not a significant change in likelihood of using shared e-scooter/bicycle ($\chi 2$ (4, N = 100) = 3.49, p =.481), public transit ($\chi 2$ (4, N = 100) = 4.12, p =.390), or Uber/Lyft ($\chi 2$ (4, N = 100) = 2.12, p =.714) before versus during the pandemic. For each Groups 2 and 3, there was a significant difference in public transit (Group 2 $\chi 2$ (4, N = 100) = 22.19, p <.001; Group 3 $\chi 2$ (4, N = 100) = 24.79, p <.001) and Uber/Lyft (Group 2 $\chi 2$ (4, N = 100) = 18.73, p <.001; Group 3 $\chi 2$ (4, N = 100) = 21.09, p <.001) usage before versus during the pandemic, but not for shared e-scooter/bicycle (Group 2 $\chi 2$ (4, N = 100) = 7.61, p =.107; Group 3 $\chi 2$ (4, N = 100) = 4.08, p =.395).

5.3.3 Changes Across Modes - Survey Data

Data was also analyzed for how likely participants were to use the various shared modes (bicycle/scooter, public transit, Uber/Lyft) before, during, and intentions after the pandemic. This

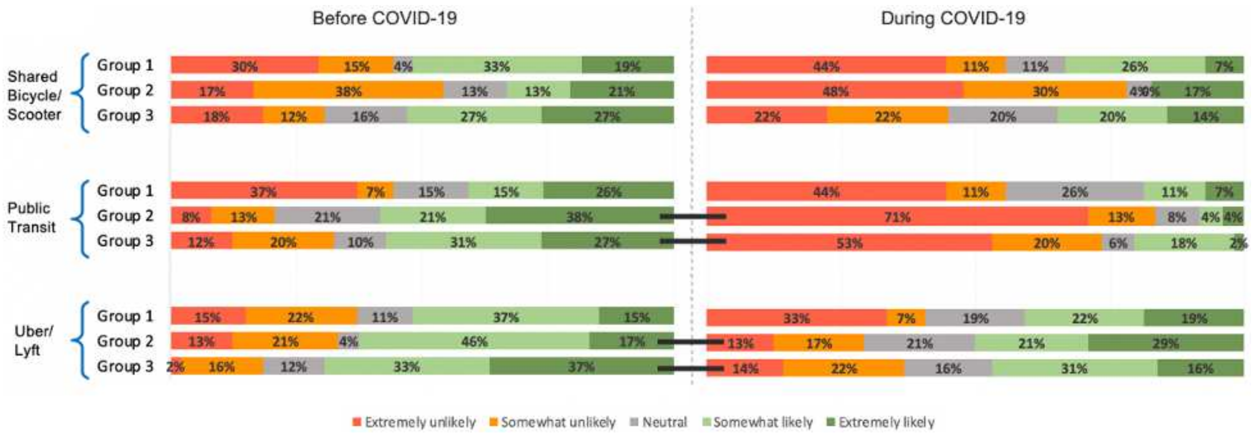

Figure 5.2: Preferences of mode choice by quarantine group, where lines connecting before and during within a group denotes significant difference.

analysis was conducted across all participants, not binned into quarantine behavior groups, see Figure 5.3. The number of favorable responses (i.e., somewhat or extremely likely to use) before versus after the pandemic remained relatively constant for each of the three modes, where transit and Uber/Lyft were slightly less favorable compared to before, while bicycles/e-scooters were slightly more favorable compared to their respective before. Favorable responses abruptly dropped during the pandemic, where the likelihood of using public transit decreased the most, followed by rideshare, then shared bicycle/scooter.

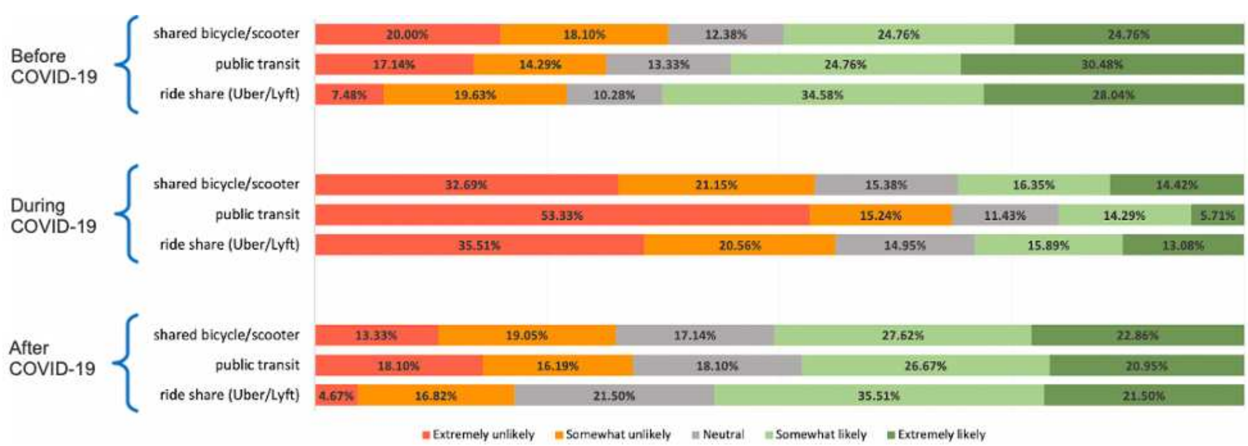

Figure 5.3: Comparison between preferences of different transportation modes.

Chi-square tests for independence were performed to further examine the relation between participants' preferences for each transportation mode and the different timeframes (before/during and before/after). Hence, a 2 (before, during) x 5 (extremely unlikely, somewhat unlikely, neutral, somewhat likely, extremely likely) chi-square test was conducted for each shared bicycle/scooter, public transit, and ride share (Uber/Lyft). Then, a 2 (before, after) x 5 (extremely unlikely to extremely likely) chi-square test was conducted for each mode.

There was no significant association between shared bicycle/scooter usage before and during the pandemic, $\chi 2$ (4, N = 105) = 8.433, p = .0769. Although people reported less intention to use shared bicycles/scooters during the pandemic, it was not significant. People's preference for public transit before and during was significant, $\chi 2$ (4, N = 105) = 40.440, $p < .05$, indicating that the pandemic significantly influenced people's choices to avoid public transit during COVID-19. The results also showed that there was a significant link between people's preferences for choosing ride share (Uber/Lyft) before and during the pandemic, $\chi 2$ (4, N = 107) = 33.74, $p < .05$, also indicating that the pandemic significantly influenced people's choices to avoid ride share. Participants' stated preferences for each mode of transportation did not differ significantly before and after COVID-19 ($p > .05$).

5.3.4 E-Scooter Trip Duration and Quantity

After data cleaning, there were 2,044 scooter trips with an average ride of 6.7 minutes in 2020 (before pandemic) and 560 trips with an average ride of 7.9 minutes in 2021 (during pandemic), see Table 5.3.

An ANOVA was performed to evaluate the difference in ride count by day of week (7 levels, Monday – Sunday) and year (2 levels, 2020 and 2021). There was no significant effect for day of week ($p > .05$), but there was a significant difference in ride count by year, $F(1, 6) = 28.7$, p = .002. As the results show, the number of rides decreased by 73% during the pandemic compared to pre-pandemic.

Table 5.3: Trip durations (in minutes) and count across study period.

Weekday	Before Pandemic (2020)					During Pandemic (2021)				
	N	Mean	SD	Min	Max	N	Mean	SD	Min	Max
Mon	346	6.7	8.5	1.0	79.3	61	6.6	7.1	1.6	23.4
Tues	314	6.5	9.9	1.0	69.5	120	7.3	6.9	1.4	112.1
Weds	392	5.6	11.0	1.0	39.8	98	8.6	4.5	1.3	39.1
Thurs	296	6.3	7.1	1.0	75.1	113	11.9	8.0	0.6	52.4
Fri	347	6.4	6.9	1.0	124.8	79	5.5	8.5	1.2	33.7
Sat	183	8.9	4.5	1.5	91.4	37	7.5	9.9	2.0	77.8
Sun	166	8.5	8.0	1.1	83.8	52	5.6	11.0	1.2	18.9
Week	**2044**	**6.7**	**7.8**	**1.0**	**124.8**	**560**	**7.9**	**8.8**	**0.6**	**112.1**

Trip duration was also evaluated using a 7 (day of week) x 2 (year) ANOVA. This distribution of trip durations across year and day is visualized in Figure 5.4. There was a significant difference in mean trip duration by weekday, $F(6, 2596) = 10.9$, $p < .0001$, where Saturday and Sunday had significantly longer trips than the weekdays. Also, average trip duration was significantly shorter for 2020 (Mean = 6.70) than 2021 (Mean = 7.97), $F(1, 2596) = 11.2$, $p = .0008$.

5.4 Discussion

This chapter evaluated how COVID-19 affected people's perception and decision towards different transportation mode choices with an emphasis on shared e-scooters. A total of 2,604 e-scooter trips in a medium-sized US city [Fort Collins, Colorado] were compared from pre-pandemic (Jan 25-31, 2020) to a similar week during pandemic (Jan 25-31, 2021). In addition, 134 survey responses from e-scooter riders and non-riders in this same city were analyzed. Survey respondents' stated quarantine behavior was also considered in analysis.

On weekends (Saturdays and Sundays) in January 2020 and 2021, the average temperature was higher (36 °F to 42 °F) than on weekdays (17 °F to 38 °F), however, Saturdays and Sundays had the lowest number of rides, but duration of rides was longer. One possible explanation is that people might use e-scooters for work/school purposes on weekdays, but for recreational trips on weekends. This finding is consistent with a case study in Austin, Texas regarding e-scooter usage

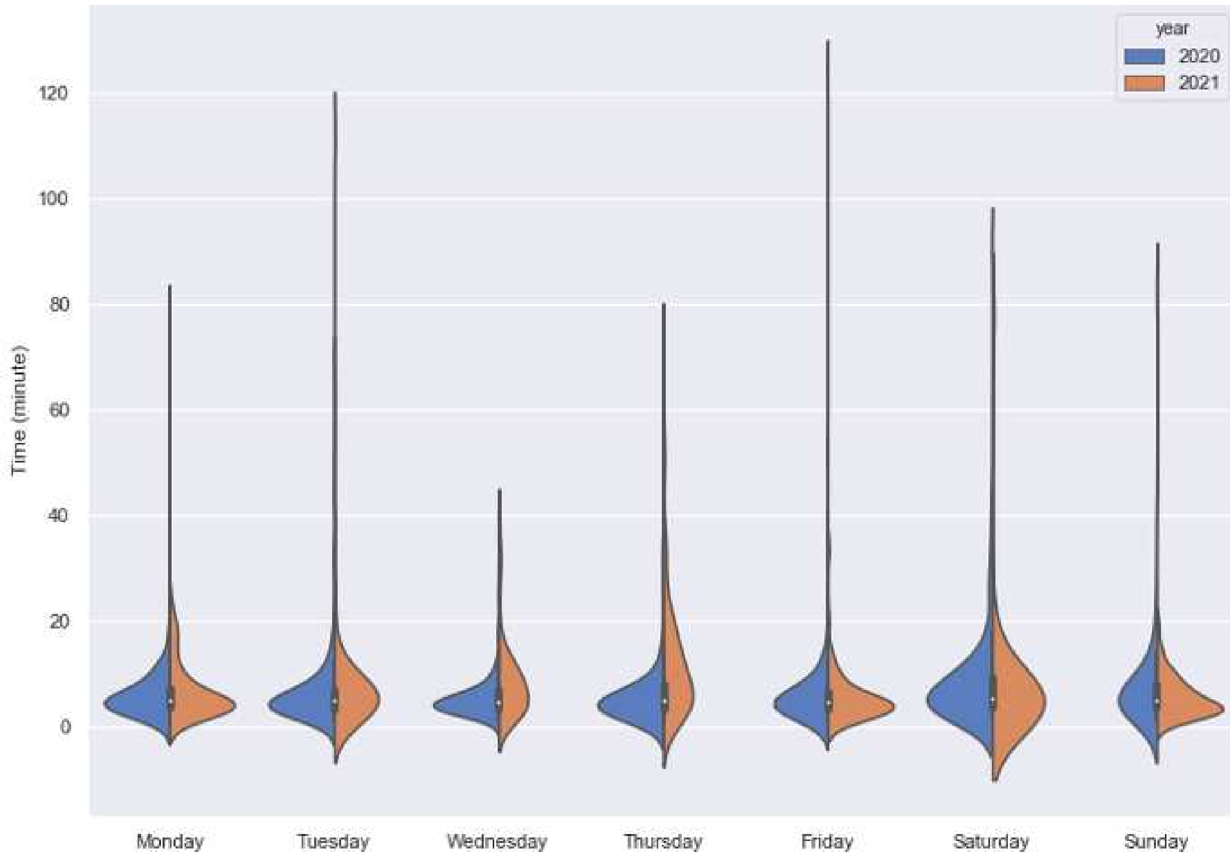

Figure 5.4: Scooter trip duration distributions before (2020) and during (2021) COVID-19.

patterns, which reported that students are a major source of users (Caspi et al., 2020). Another consideration is that people might be solving parking limitations during the weekdays by replacing their short commutes with e-scooter trips. A study by (Guo & Zhang, 2021) supports this, where they explain that inconvenience of parking is a cause of converting from driving to shared e-scooters and bicycles.

During the pandemic, e-scooter trip durations were longer than before the pandemic. Additionally, participants reported the least intention to use public transit during COVID-19. It is possible that people were using e-scooters to travel distances that had previously been covered by public transportation. This is supported by (Li et al., 2020), who reported that a portion of public transportation trips were replaced by e-scooter trips. Another possible explanation for these longer e-scooter trips could be that scooter users felt safer riding for longer distances on roads with fewer vehicles. This is also supported by previous research that shows the flow rate of vehicles during the pandemic decreased, and this traffic reduction had a positive impact on road safety (Harantová, Hájnik, & Kalašová, 2020). Therefore, having a shared lane with other vehicles or no designated lane for micromobility users, might be a discouraging factor for users.

Participants were grouped based on their quarantine behavior, into 'left house similarly to before pandemic' (Group 1), 'only left house for essential activity' (Group 2), and 'only left house for essential activity and work' (Group 3). Travel behavior before and during COVID-19 was compared between these groups. Groups 2 and 3 reported significantly different uses of public transportation and Uber/Lyft before versus during the pandemic, while Group 1 reported consistent mode choice before compared to during the pandemic.

Most participants, regardless of quarantine behavior group, had no strong opinion towards the hygiene level of the shared micromobilities, where most responses were 'neutral' regarding their perception of sanitary level of shared e-scooters and shared bicycles. This lack of a strong opinion either direction suggests that people could be unaware and lack information about policies and practices by shared micromobility operators. As such, there is an opportunity for companies to inform potential users (e.g., hang hand-sanitizer from scooter, inform riders through the mobile application) about sanitation practices and this could be an encouraging and effective factor. Previous studies have shown that sanitation plays a significant role in people's behavior and decision-making. According to a survey study in Indonesia, 95.3% (N = 854) of participants reported high intention to continue their COVID-19 hygiene behavior post pandemic (Dwipayanti, Lubis, & Harjana, 2021). Additionally, according to a study by (Jahanshahi, Gashti, Mirdamadi, Nawaser, & Khaksar, 2011), informing customers about increased sanitary levels of equipment will increase customer satisfaction and loyalty. Therefore, fostering transparency about the sanitation of shared micromobilities can have a positive effect on trust, and consequently, on the usage of these transport modes.

A potential limitation with this research is that it was conducted in a college town in the U.S. with a high proportion of student residents. Even though the results of this research are consistent with larger studies in this field, further research should consider different student to non-student composite populations. As students often have more limited transportation mode options.

5.5 Conclusions

In this chapter, e-scooter trip and survey data was evaluated to understand perceptions and preferences in choosing various transportation modes in relation to the COVID-19 pandemic, with an emphasis on e-scooters. Comparable weeks before and during the pandemic were selected for e-scooter trip analysis. The survey, which was administered during the pandemic, asked about behavior before, during, and their intentions after the pandemic. ANOVAs were performed to evaluate the relationships between number of rides and trip durations between the two time periods (before/during). Chi-square tests of independence were used to determine whether there was a relation between perceptions and preferences for each shared mode of transportation across the different time periods (before/during/after).

More e-scooter trips occurred on weekdays than on weekends, but trips on weekends were 47% longer. There were 73% less rides during the pandemic, but the rides were 19% longer. In this study, about one quarter of the participants left their house similar to before the pandemic, another quarter left their house only for essential activity, and half left only for essential activity and work. The group that left their house similar to before the pandemic had no change in their use of shared modes. While the groups that quarantined reported using less public transit and less Uber/Lyft during the pandemic. Overall, the reported likelihood of using a particular mode remained almost the same for before and after the pandemic.

This study uniquely describes the effect of the pandemic on shared transportation modes, particularly for micromobility options. These insights relate to behavior and perceptions before, during, and intentions for after the pandemic. Investments in infrastructure supporting micromobility, subsidies, and public awareness campaigns can promote micromobility adoption during potential future pandemics or threats, contributing to a more resilient and inclusive transportation system. As such, these results and analytical framework can be beneficial for researchers, policymakers, and operators to make data-driven decisions regarding safety and sustainability to better understand this emerging class of mobility systems, especially as post pandemic travel habituates.

Chapter 6

RQ3: Drivers' Personality Factors on Interactions

6.1 Introduction

Previous literature suggests that drivers' personality and emotions may influence their interactions with vulnerable micromobility users, such as bicyclists and pedestrians. This chapter seeks to extend the existing body of research by focusing on the roles of driver risk-taking tendency and emotional intelligence on passing bicyclists and yielding to pedestrians. These findings aim to enhance the coexistence of drivers and micromobility users, thereby improving safety and efficiency within urban transportation networks.

This chapter addresses Research Question 3: How does risk-taking propensity and emotional intelligence of drivers impact their interactions with bicyclists and pedestrians? Forty participants completed a driving simulator drive, where they experienced three passing events each of a single bicyclist on the road, single bicyclist in the bike lane, and group of bicyclists in the bike lane, and one mid-block pedestrian crossing. Risk-taking and emotional intelligence were measured using a survey.

The results of this chapter are currently under review for publication in a peer-reviewed journal.

6.2 Methods

To examine the impact of drivers' risk-taking behaviors and emotional intelligence on their interactions with bicyclists and pedestrians, a driving simulator study was conducted.

6.2.1 Participants

The sample comprised of 40 participants who were recruited using flyers posted around Colorado State University. Inclusion criteria required participants to be at least 18 years of age and possess a valid US driver's license.

There were 31 males, 8 females and 1 prefer not to answer, with an average age of 29.8 years (min = 18, max = 52, SD = 8.1). The average length of time for having a driver's license among the sample was 10.1 years (min = 0.75, max = 35, SD = 7.9). The highest level of education completed by the participants was as follows: less than high school (N = 1), high school (N = 1), some college (N = 5), bachelor's degree (N = 12), and post-graduate degree (N = 21).

6.2.2 Driving Simulator

A fixed-based miniSim quarter cab was used for the experiment (see Figure 6.1). The simulator provides 140 degrees of horizontal field of view via three 48-inch monitors. Participants completed a 3-minute practice drive in the simulator, and then completed the 6-minute study drive.

Figure 6.1: Participant (head intentionally obscured) in the driving simulator scenario.

The scenario environment was a modified version of the Driving Safety Research Institute's Springfield Road Network. The scenario comprised of urban streets, with several traffic signals, light vehicle traffic, some pedestrians, some bicyclists, and a speed limit of 40 miles per hour (mph). The first approximately 3.5 minutes of the drive was along a 4-lane (2-lanes in each direction) road with a dedicated bicycle lane and sidewalk on each side. The last approximately

2.5-minutes of the drive was along a 2-lane (1-lane each direction) road with sidewalks but no bicycle lanes. Example screenshots of the Springfield Road Network are provided in Figures 6.2 and 6.3.

Figure 6.2: Example Springfield Road Network Pedestrian Crossing.

Participants received written navigation instructions displayed on the simulator screen about when to turn. They also received a written message saying, “Speeding Alert: Please Slow Down!” whenever they exceeded the speed limit by 10 mph.

During the drive, participants experienced nine bicycle passing events and one pedestrian crossing event. Specifically, each participant passed a single bicyclist riding in the bicycle lane three times, a single bicyclist riding in the right lane three times, and a group of six bicyclists riding in the bicycle lane three times. In the data, each bicycle passing event was coded as 3-seconds before through 4-seconds after the vehicle passed the bicycle. Shortly after each interaction with a bicycle, a slow-moving vehicle was positioned in the left lane, such that participants would return to the right lane (i.e., adjacent to the bicycle lane) if they had changed lanes to pass the cyclists. There was never a vehicle immediately to the left of the participants while they were passing a cyclist, such that they could provide lateral space between their vehicle and the bicycle if they wanted. During the portion of the drive along the segment of the 2-lane road, participants encountered a mid-block crosswalk with two pedestrians waiting to cross and another pedestrian already three-

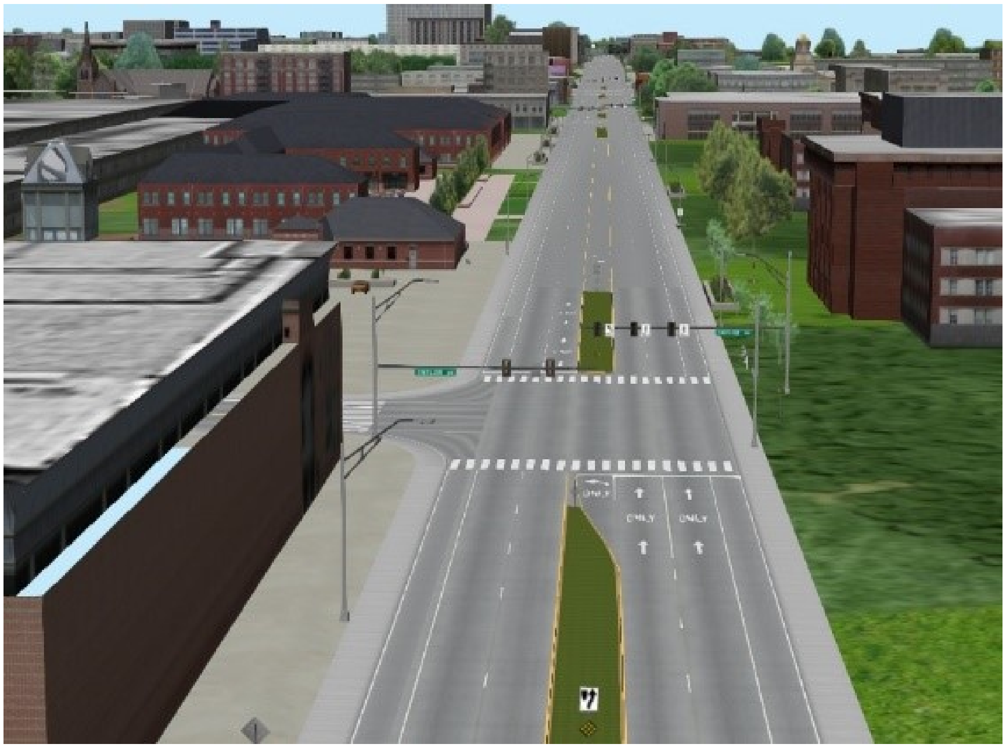

Figure 6.3: Example Springfield Road Network Empty Roadway.

quarters of the way crossed, on the other side of the street. Hence, they could continue through without hitting a pedestrian, or stop and yield to the pedestrians waiting to cross. A screenshot showing an example of bicyclists in the simulator is provided in Figure 6.4.

Figure 6.4: Example Springfield Road Network View of Bicyclists from Vehicle.

6.2.3 Questionnaires

Prior to driving in the simulator, participants completed an emotional intelligence (EI) survey, which had 30 questions using a 7-point Likert scale. The survey was an adaptation of the Trait

Emotional Intelligence Questionnaire – Short Form, TEIQue-SF (Cooper & Petrides, 2010) for use in the driving context, where this adaptation has been validated in previous work (Buehler et al., 2021; Almannaa et al., 2021; Ahmed & Miller, 2023; Ahmed, Ward, Otto, McMahill, & Miller, 2023). Participants were not told that the survey measured EI, but rather asking about their typical driving experiences. It is important to note that certain questions in the EI scale were intentionally reverse-scored. This technique was used to minimize response bias and provide quality control, ensuring that participants could not simply select the same response (e.g., "strongly agree") for all items without carefully considering each statement. During data analysis, these reverse-scored items were recalibrated to accurately compute the total EI values, thereby providing a more valid assessment of participants' emotional intelligence.

After completing the drive, participants completed one more survey, which collected information on demographics, risk propensity using the General Risk Propensity Scale, GRiPS (D. C. Zhang et al., 2019), and about their general driving experiences, focusing on interactions with bicyclists. A copy of this survey is provided in Appendix C.

6.2.4 Procedure

Participants first completed the EI survey on a computer. Then they were explained how the driving simulator worked, performed the practice drive, and then completed the study drive. Participants were told to drive the posted speed limit [of 40 mph], to drive in the right lane whenever possible, and that navigation instructions would appear on the screen. They were told the purpose of the study was to collect data on how people drive through a city environment. After the drive, they filled out the second survey [on risk and driving experience] on the computer. The entire study took approximately 20-minutes per participant.

6.2.5 Analytical Methods

Data analysis and cleaning was performed using Python (version 3.6.12) and RStudio (R version 4.3.2). Generalized linear models were used to predict driving behaviors based on risk-taking and EI. Specifically, linear mixed models were used to predict driving speed variables for the bicycle interaction events. These models included random effects for the participant, as there were multiple observations per participant. Additionally, a binary logistic regression model was used to predict braking during the pedestrian interaction event. Lastly, chi-squared tests were used to compare differences in survey responses across risk groups.

Dependent Variables

A linear mixed model was fit on each of the following dependent variables:

- *Average Speed During Bicycle Passing Event (mph):* Average driving speed during the 7-second time interval during the passing event.
- *Speed at Passing Instance (mph):* Driving speed at the exact time when the vehicle passed the bicycle. This was extracted from the data based on the observation for which the minimum distance to the bicycle was the smallest.
- *Distance to Bicycle at Passing Instance (inches):* Minimum lateral distance of the vehicle to the bicycle(s) during the passing instance.

One binary logistic model was fit on the following dependent variable:

- *Applied Brakes for Pedestrians (yes/no):* Whether the participant applied the brakes and slowed down to less than 25 mph when the crosswalk became visible.

Independent Variables

The following variables were included as fixed effects in the models:

- *Risk-Taking:* Average score across risk questions (GRiPS survey), where a larger value indicates more risk-seeking tendencies.
- *Total EI:* Average score across EI questions (DEIS survey), where a larger value indicates higher EI.

- *Bicycle Passing Event:* Three scenarios - bicyclist in bike lane, bicyclist on road, group of bicyclists in bike lane.

6.3 Results

6.3.1 Participant Characteristics

Most of the participants report using a bicycle often, where 11 (27.5%) bicycle daily, 6 (15%) weekly, 10 (25%) a few times a month, 12 (30%) a few times a year, and 1 (2.5%) never. Similarly, most of the participants are frequent drivers, where 26 (65%) drive daily, 5 (12.5%) weekly, 2 (5%) a few times a month, 6 (15%) a few times a year, and 1 (2.5%) never.

Risk-taking scores from the GRiPS survey were computed based on their average across the eight questions, which yields one total risk-taking value for each participant, with possible ranges from 1 (risk-adverse) to 5 (risk-seeking). In our sample, we observe total risk-taking scores ranging from 1 (N = 2) to 4.5 (N = 3), and a mean of 2.9 (SD = 1.1).

EI scores were computed as a composite score ('Total EI') for each participant, based on the average of their responses across the EI questions, with possible ranges from 1 (lower EI) to 7 (higher EI). Observed values in this study range from 3.7 to 5.3 (mean = 4.7, SD = 0.4).

6.3.2 Braking for Pedestrians

A binary logistic model was fit to predict braking for pedestrians waiting to cross at a mid-block crosswalk based on total EI and risk-taking (see Table 6.1). Only fixed effects are included in this model, as there is only one pedestrian event per participant (i.e., no repeated measures). The model suggests that there is a significant effect of risk-taking, where participants are less likely to break (i.e., not yield) for increased risk-taking scores. Specifically, the odds ratio (exponent of β) indicates that for each one unit increase in risk-taking, the odds of braking decrease by a factor of 0.4 (95% confidence interval of 0.14 to 0.87).

Table 6.1: Summary Predicting Braking for Pedestrians.

Variable	Estimate	Std Error	t-value	p-value
(Intercept)	8.60	6.22	1.38	.167
Risk-Taking	-0.92	0.45	-2.06	.039
Total EI	-1.01	1.19	-0.86	.393
Model Fit	*LL*	*DF*	*Chi-Sq*	*p-value*
Model	-20.7	3	5.7	.05
Null	23.5	1		

6.3.3 Speeds When Passing Bicycles

Each participant passed a cyclist on the road three times, a cyclist in the bike lane three times, and a group of cyclists in the bike lane three times. These passing events were analyzed for the 7-second interval and the exact moment of passing for each event.

Average Speed During Bicycle Passing Event

A linear mixed model was fit to predict average driving speed during the passing event based on total EI, risk-taking, and passing event type (see Table 6.2). The model shows a significant effect of risk-taking on speeding, where each unit increase of the risk-taking score is associated with an increase of 4.02 mph during the passing event. There is also a significant effect of passing event type, where participants drive, on average, slower for a cyclist on the road (2.52 mph slower) and slower for a group of cyclists in the bike lane (2.33 mph slower), as compared to passing a cyclist in the bike lane. There is no effect of EI on average speed.

Speed At Bicycle Passing Instance

A linear mixed model was fit to predict driving speed at the exact time of passing based on total EI, risk-taking, and passing event type (see Table 6.3). This model output is consistent with the previous model on average speed. Specifically, participants that are more likely to take risks are also more likely to drive faster at passing (3.78 mph increase for each unit increase of risk-taking score). Additionally, participants drive slowest when passing a single bicyclist on the road (3.98

Table 6.2: Summary Predicting Average Speed While Passing.

Variable	Estimate	Std Error	t-value	p-value
(Intercept)	30.49	27.58	1.11	.270
Risk-Taking	4.02	1.86	2.16	.037
Total EI	1.09	5.59	0.19	.847
Passing Event (ref: bike in bike lane)				
Bike on Road	-2.52	0.96	-2.62	.009
Group of Bicyclists	-2.33	0.96	-2.42	.016
Model Fit	*AIC*	*LL*	*L Ratio*	*p-value*
Model	2591.6	-1288.8	24.6	$< .001$
Null	2608.2	-1301.1		

mph slower) and slower when passing a group of bicyclists in the bike lane (2.68 mph slower) as compared to a single bicyclist in the bike lane. There is no significant effect of EI.

Table 6.3: Summary Predicting Speed at Passing Instance.

Variable	Estimate	Std Error	t-value	p-value
(Intercept)	31.32	27.73	1.13	.260
Risk-Taking	3.78	1.87	2.02	.050
Total EI	1.61	5.62	0.29	.776
Passing Event (ref: bike in bike lane)				
Bike on Road	-3.98	1.21	-3.30	.001
Group of Bicyclists	-2.68	1.21	-2.22	.027
Model Fit	*AIC*	*LL*	*L Ratio*	*p-value*
Model	2736.5	-1361.2	27.7	$< .001$
Null	2756.2	-1375.1		

6.3.4 Distance When Passing Bicycles

A linear mixed model was fit to predict minimum distance to the bicycle(s) during each passing instance. In addition to the fixed effects of EI and risk-taking, speed at the passing instance is included as an independent variable to account for possible compensatory behaviors (see Table 6.4). The model shows a significant effect of speed at passing on distance to the bicycle. Specifically, as driver speed increases, their passing distance to the bicycle decreases. This suggests that people drive faster when they are laterally closer to the bicyclists, compared to farther away [laterally].

Table 6.4: Summary Predicting Minimum Distance at Passing Instance.

Variable	Estimate	Std Error	t-value	p-value
(Intercept)	16.70	12.55	1.33	.184
Risk-Taking	0.53	0.86	0.62	.537
Total EI	0.73	2.53	0.29	.775
Speed at Passing	-0.10	0.04	-2.22	.027
Passing Event (ref: bike in bike lane)				
Bike on Road	-1.53	1.15	-1.32	.187
Group of Bicyclists	1.39	1.15	1.22	.225
Model Fit	*AIC*	*LL*	*L Ratio*	*p-value*
Model	2646.2	-1315.1	15.6	.008
Null	2651.8	-1322.9		

6.3.5 Perceived Comfort Passing Bicycles

The association between risk scores and stated preferences were further investigated, based on the significance of risk on observed behaviors in the driving simulator. Specifically, we categorized participants into three distinct risk groups based on quartiles of the sample's risk-taking scores: 1) Risk Avoidant (N = 14), average score below 25th percentile (i.e., ≤ 2); 2) Moderate (N = 14), average score between 25th and 75th percentiles (i.e., 2.01 to 3.99); and 3) Risk Taker (N = 12), average scores above 75th percentile (i.e., ≥ 4).

Participants were asked, in general, to rate their comfort level as a driver when passing a bicyclist in three distinct situations: on the road (sharing the lane), in the bike lane, and on the sidewalk. Figure 6.5 illustrates the differences in these perceived comfort levels across the three risk-taking groups.

These proportions were analyzed using chi-squared tests. For the risk-takers, there is a significant effect of scenario on their comfort level; where they are significantly more comfortable passing bicyclists on the sidewalk ($\chi2$ (2, N = 12) = 6.89, p = 0.032). Similarly, the moderates

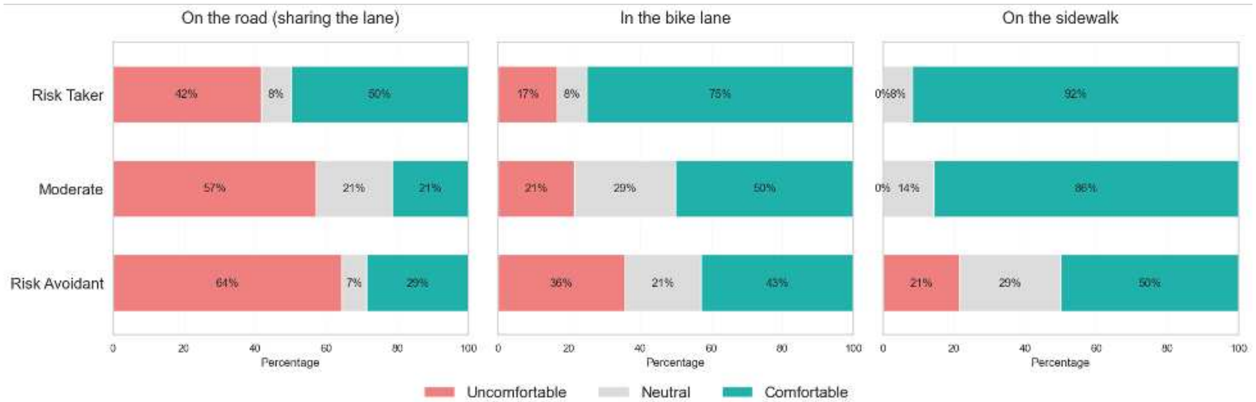

Figure 6.5: Self-reported comfort of drivers passing bicyclists based on risk-taking category and situation.

are also significantly more comfortable passing bicyclists on the sidewalk compared to the other passing scenarios ($\chi2$ (2, N = 14) = 13.73, p = 0.001). However, there was no relationship between passing scenario and comfort level for the risk-avoiders, suggesting that they were equally uncomfortable passing bicyclists across all scenarios ($\chi2$ (2, N = 14) = 3.61, p = 0.164).

6.3.6 Correlations between Driving Behaviors

A correlation analysis was conducted on the driving variables (see Figure 6.6). The analysis was conducted individually within each of the three bicycle events. The variables for each were average speed during passing, speed at passing instance, distance at passing instance, and percentage of entire drive spent speeding. Across all interaction events, there is a significant and strong positive correlation between the speed variables (i.e., average speed during the event, speed at passing instance, and percentage of total drive spent speeding). This consistency indicates that drivers tend to maintain their speed as they approach and pass bicyclists, regardless of the type of interaction.

6.4 Discussion

This chapter utilized a driving simulator to examine how risk-taking behavior and emotional intelligence impact driver interactions with bicyclists and pedestrians in urban contexts. The analysis, employing a binary logistic model, revealed a significant association between higher levels of risk-taking and decreased likelihood of braking for pedestrians. This aligns with (Martha &

Figure 6.6: Correlation matrix for driving behaviors by event, where *** denotes $p < .001$.

Delhomme, 2014), who noted that high-risk takers often possess skewed perceptions of driving risks, potentially overlooking pedestrian-related dangers due to narrowed attentional focus. This behavior might stem from cognitive biases such as overconfidence in one's driving abilities or underestimation of the unpredictability of pedestrian movements.

In this study, we utilized linear mixed models to examine the dynamics between risk-taking behavior, types of bicycle passing events, and driving speeds. Our analysis identified a significant influence of risk propensity on driving speeds. Specifically, we observed that an uptick in the risk-taking score corresponded with an increase in driving speed, both during the overall interaction and specifically at the moment of passing bicyclists. This trend not only highlights the direct impact of risk-taking tendencies on speed regulation but also corroborates existing literature which suggests that individuals with higher risk-taking profiles are predisposed to engage in speeding (Ulleberg & Rundmo, 2002). This finding reinforces the notion that risk-taking is a key determinant in aggressive driving behaviors, potentially escalating the likelihood of crashes during interactions with vulnerable road users.

In our investigation of how the type of passing event affects driver behavior towards cyclists, the results demonstrated a significant difference in both the speed at the moment of passing and the average speed during the interaction, contingent upon the event type. Drivers were observed to moderate their speeds more when passing a cyclist directly on the road, with an even more pronounced reduction in speed when encountering a group of cyclists within a bike lane. This behavior suggests a heightened awareness and caution when more people are present in the driving environment.

The presence of dedicated bike lanes appears to play a crucial role in shaping these behaviors. When cyclists are physically separated from motor vehicle traffic, drivers likely perceive a lower risk of collision, leading to reduced anxiety and a safer interaction dynamic. This hypothesis is supported by the work of (Reynolds, Harris, Teschke, Cripton, & Winters, 2009), who noted that purpose-built bicycle-specific infrastructure, like bike lanes, significantly decreases the likelihood of crashes and injuries by providing a dedicated and predictable space for cyclists, thereby enhancing mutual road user predictability.

Further supporting this observation, (Deliali, Campbell, Knodler, & Christofa, 2020) found that drivers are less attentive to cyclists in scenarios where protected bike lanes separate them, likely due to the perceived security provided by the physical barriers. This could lead to a paradox where drivers, feeling overly secure due to the infrastructure, might pay less attention to potential crossing points or emerging cyclists. However, the overall impact of such infrastructure on road safety is undeniably positive, as evidenced by reduced crash rates and improved safety metrics. Moreover, a roadway design survey conducted by (Sanders & Judelman, 2018) reinforces the notion that the presence of separated bike lanes not only alters driver behavior but also enhances their perceptions of safety. This perceived safety likely contributes to more cautious driving behaviors when drivers approach these well-defined and separated spaces. These findings underscore the importance of intentional urban and transportation planning that incorporates dedicated cycling infrastructure. Such infrastructure not only provides physical safety benefits but also psychologically impacts drivers, encouraging them to adopt more cautious driving behaviors near cyclists. This dual benefit is crucial for developing holistic road safety strategies that accommodate the growth of cycling in urban centers and ensure the safety of all road users.

Our findings also indicate that as the number of cyclists in a passing event increase, drivers tend to decrease their speed, suggesting a perceived higher risk when navigating around groups of cyclists. This behavioral adjustment may stem from drivers allocating more attention to the multiple dynamic factors present when multiple cyclists are involved. The presence of a group requires drivers to anticipate a variety of possible actions from different cyclists, necessitating a more cautious driving approach. Additionally, the variability in cyclists' behavior within these groups may compel drivers to adapt their driving strategies more conservatively, effectively reducing their passing speed to accommodate the unpredictable nature of the group's movement. This adaptation is crucial in complex traffic environments where the likelihood of sudden changes in the road scene increases.

Supporting this observation, (Hoekstra, Twisk, & Hagenzieker, 2018) noted that drivers who also engage in cycling tend to exhibit greater empathy and awareness towards cyclists. This alignment with the 'safety in numbers' theory suggests that an increase in cyclist presence on the roads can lead to safer conditions for cyclists overall, as drivers become more attuned and habituated to sharing the road with them. Such findings reinforce the value of dedicated bike lanes and other cyclist-specific infrastructure in enhancing road safety by clearly delineating cyclist spaces and improving driver awareness and behavior towards cyclists.

It is important to note that participants were given specific driving instructions during the experiment, such as maintaining a specific speed limit and lane discipline. This may have restricted natural driving behaviors that occur in less controlled environments. Future research could benefit from utilizing similar performance measures in naturalistic driving settings.

6.5 Conclusions

This chapter offers valuable insights into how risk-taking behavior influences driver interactions with bicyclists and pedestrians under urban driving conditions. Utilizing a driving simulator experiment, we establish a clear link between risk-taking tendencies and specific driving behaviors. It is notably apparent that drivers with higher risk-taking scores are less inclined to brake for pedestrians and exhibit increased speeds while passing bicyclists. These behaviors suggest a potential disregard for established safety norms and underscore the importance of addressing such tendencies in road safety programs. Moreover, our findings reveal that the nature of bicycle passing events, whether passing a cyclist on the road or a group in a bike lane, significantly affects driving speed. This indicates that drivers adjust their behavior based on the perceived complexity and risk of the traffic environment, showcasing a nuanced understanding of situational driving dynamics.

Although emotional intelligence did not significantly influence driving behaviors in this study, the overall results emphasize the need for targeted road safety interventions. By integrating knowledge of individual risk profiles and environmental factors, policymakers and safety advocates can develop more effective strategies to enhance safety for all road users in urban settings.

Chapter 7

Other Significant Work During PhD

During my PhD, I was involved in several collaborative projects that led to important publications in energy efficiency, transportation safety, and telemedicine. These collaborations enriched my research experience and broadened my skill set with applications to real-world issues. This section presents an overview of these key projects. It emphasizes the diverse methodologies employed and the substantial contributions these studies made to their respective fields.

7.1 User Perceptions of Automated Truck-Mounted Attenuators: Implications on Work Zone Safety

Automated Truck-Mounted Attenuators (ATMAs) have the potential to improve work zone safety by removing the human driver out of a vehicle that is positioned in work zones to absorb impact from errant vehicles. However, this automated technology is expensive and can be detrimental to safety and project success if operated incorrectly (e.g., operating limitations and procedures not followed). Therefore, it is important to understand users' perceptions of ATMAs and how training can improve appropriate adoption of this technology. The objective of this study was to evaluate how work zone workers perceive the usefulness of and the capabilities of automation in Truck-Mounted Attenuators.

A survey study was conducted with 13 Department of Transportation (DOT) workers in Colorado and California. Each of the DOT workers in this study had some previous experience with the ATMA, either in real-world applications and/or formal training. The survey collected information on participant job specifications, experience with the ATMA, training received, trust in the ATMA, usability of the HMIs, and operating capabilities of the automation.

Workers reported an overall positive acceptance of this technology. This was supported by their expectation that it would reduce crash severity; that there was a reasonable workload associated with operating procedures for the automation; and by their overall trust in the automation's reliability. However, workers noted concerns regarding their trust in the automation under various contexts, such as poor visibility and denser traffic volumes. Further, trust in the technology was greatest among workers with higher levels of ATMA training and longer experience working with the ATMA.

This research presents a novel perspective on user acceptance of ATMA technology. These findings can help jurisdictions achieve the safety improvements that investment and deployment of automation in work zones offers, by identifying the disconnect between operators and technology

This research was funded by the Autonomous Maintenance Technology Pooled Fund and in collaboration with the Colorado Department of Transportation (CDOT). I was the lead student on this project, and my primary role was survey development, data analysis, and report writing. This work was published in the *Journal of Traffic Injury Prevention* (Pourfalatoun & Miller, 2021b) and as a technical report with CDOT (E. E. Miller, Pourfalatoun, Nylen, & Weldon, 2021). In addition, this work was presented as a poster at the *Transportation Research Board (TRB) Annual Meeting* in 2021 (Pourfalatoun & Miller, 2021a).

7.2 Applying the Heteroskedastic Ordered Probit Model on Injury Severity for Improved Age and Gender Estimation

Driver characteristics have been linked to the frequency and severity of car crashes. Among these, age and gender have been shown to impact both the possibility and severity of a crash. Previous studies have used standard ordered probit (OP) models to analyze crash data, and some research has suggested heteroskedastic ordered probit (HETOP) could provide improved model fit.

In this study, the potential improvements of the heteroskedastic ordered probit (HETOP) model over the standard ordered probit (OP) model in crash analysis were evaluated, focusing on the effect of gender across age on injury severity among drivers. It was hypothesized that the HETOP model could provide a better fit to crash data by allowing for heteroskedasticity in the distribution of injury severity across driver age and gender.

Data for 20,222 crashes were analyzed for North Carolina from 2016 to 2018, which represents the state with the highest number of fatalities per 100 million vehicle miles traveled amongst available crash data from the Highway Safety Information System.

It was found that darker lighting conditions, severe road surface conditions, and less severe weather were associated with increased injury severity. The probability of severe injuries was observed to increase with age and for male drivers. Furthermore, the variance of severity was found to increase with age disproportionately within and across genders, and the HETOP model was capable of accounting for this heteroskedasticity.

The results revealed that the HETOP model outperformed the standard OP model in measuring the effects of age and gender together on injury severity, due to the heteroskedasticity within gender and age. It was concluded that the HETOP statistical method can be more broadly applied across other contexts and combinations of independent variables for improved model prediction and accuracy of causal variables in traffic safety.

This research was in collaboration with two researchers from the Department of Transportation & Urban Infrastructure Studies at Morgan State University in Baltimore, Maryland. My role on this project was to assist in data analysis and report writing. The results of this research were published in the *Journal of Traffic Injury Prevention* (Nickkar, Pourfalatoun, Miller, & Lee, 2024).

7.3 Energy Labels Affect Behavior on Rental Listing Websites: A Controlled Experiment

When renters seek new homes, they often lack critical information regarding the energy costs associated with the property. This absence of information can result in significant financial strain post-move and complicates their ability to effectively manage household budgets. Conversely, landlords face no penalties for maintaining energy-inefficient properties, thereby reducing their incentive to make necessary energy efficiency improvements to their rental units.

This study examined whether including energy efficiency or energy cost information in rental listings would influence renters' decisions on where to live. The objective was to understand how much renters value energy efficiency when searching for homes and how their choices might change if rental listings included this information.

The impact of energy efficiency labels on renters' decision-making within rental listing platforms was investigated through a controlled discrete choice experiment. A mock website, designed to replicate real-world rental search conditions, was employed to analyze how different formats of energy efficiency labels influenced renters' preferences. Participants, drawn from a nationally representative sample, were exposed to these labels, and their selections were meticulously recorded.

This study found that energy labels on rental listings significantly change renters' property preferences. In a simulated rental listings website, the presence of energy labels prompted a nationally representative sample of renters to choose the most efficient listings 21% more often, while the least efficient option was chosen 21% less often when energy efficiency information was hidden.

The findings also indicated that energy efficiency labels providing additional context information (such as how one home compares to others or to a maximum score) are more effective in influencing renter behavior than those offering less context. Labels that compare the efficiency of homes (houses and apartments) to similar properties are particularly persuasive. For example, displaying estimated energy costs on a scale of minimum to maximum is more impactful than presenting energy costs without such a continuum.

Additionally, the study revealed that renters seeking apartments, those living in extreme climates, and younger renters (under 45) were willing to accept higher rent in exchange for improved energy scores. Renter income was not a factor in this simulation, even for individuals with low incomes or those who allocate a significant portion of their income to energy expenses.

This study emphasizes the potential of mandatory energy labeling policies in rental markets to enhance energy awareness among renters and drive broader efficiency improvements in the housing sector. I assisted with the data analysis and the survey design for this study. Our cross-functional collaboration between Colorado State University and American Council for an Energy-Efficient Economy (ACEEE) led to innovative solutions that were featured in Bloomberg News (Bloomberg News, 2022).

7.4 Using Augmented Holographic UIs to Communicate Automation Reliability in Partially Automated Driving

In partially automated driving, drivers are expected to actively supervise the road. However, a growing body of research shows that drivers become more complacent in system operation and fail to continuously monitor the road, which results in mode confusion. Lack of transparent communication of automation mode and its level of reliability has been discussed as a main underlying cause of these challenges.

Furthermore, the complacency observed in drivers leads to lower situational awareness. This decreased situational awareness is closely linked to mode confusion, where drivers are unclear about the vehicle's operational mode. Mode confusion not only diminishes the driving experience but has also been identified in the literature as a primary cause of incidents and accidents across various domains of human-automation interaction.

Several reasons have been discussed in the current body of literature as the potential underlying factors of mode confusion. Reduction of driving workload in automated driving on one hand, and having access to several electronic devices and displays, on the other hand, encourage the driver to spend more time out of the driving loop and stay engaged in non-driving related secondary tasks (NDSTs). This insufficient monitoring behavior could lead to mode confusion. Moreover, drivers in such situations may not be well prepared to regain vehicle control when a sudden change on the road ahead (e.g., missed lane marking or a cut-in vehicle) has prompted an emergency takeover request.

Misunderstanding of the internal user interfaces (UIs) has been mentioned as another constraint in partially automated driving. Most of the current partially automated vehicles in the market use visual warning and or a combination of visual and auditory feedback to communicate automation modes. However, sometimes these modalities are not straightforward enough to communicate the status of automation, or they may not be salient enough to capture the driver's attention. Moreover, previous studies have reported the potentially confusing or startling effects of these types of warnings, especially when warnings are not presented to the driver in a timely manner.

In this study, the effects of an augmented reality lane marking (AR-LM) on driver behavior in partially automated vehicles were assessed. A controlled driving simulator was utilized to measure participants' glance behavior, takeover time in critical events, hazard detection, and perceptions of automation. Participants were divided into two groups: control and AR-LM. It was found that the AR-LM user interface significantly influenced takeover times, increased gaze time on the road, and impacted trust in automation. These results suggest that the AR-LM concept could assist drivers in maintaining visual attention to the road under low-reliability and failure conditions. However, it was also observed that this user interface might reduce hazard detection when automation is operating in high-reliability mode.

This research was conducted in collaboration with the Department of Systems Engineering at University at Buffalo (UB). My role on this project was to assist in data analysis and report writing. The results of this research were published at the *CHI 2020 Conference on Human Factors in Computing Systems* (Ebnali, Fathi, Pourfalatoun, & Motamedi, 2020).

7.5 Clinician-AI Collaboration in Telemedicine

Telemedicine has become a prominent method for delivering remote healthcare, offering numerous benefits such as improved accessibility, convenience, and cost-effectiveness. This is especially valuable in situations where in-person consultations are challenging or not feasible. As telemedicine evolves, integrating AI can further enhance the telemedicine experience and address some complexities of the modern healthcare landscape. AI systems, particularly large language models (LLMs), have the potential to revolutionize telemedicine practices by providing advanced language-related capabilities like question answering, translation, and text summarization.

The ability of ChatGPT, as a widely used LLM, to generate coherent and contextually relevant responses using large textual data presents an opportunity to improve clinical support in telemedicine. However, LLMs have inherent limitations, such as occasional inaccuracies, nonsensical content generation, and the potential for presenting misinformation as factual information. The accuracy of LLM-generated answers is closely linked to the quality, quantity, and nature of the data used in their training.

For successful integration of AI in telemedicine, understanding human trust and acceptance of AI-based clinical support is essential. Despite the increasing use of AI in medicine, there is limited research on the acceptance and trust of LLM-powered technologies in telemedicine. Prior studies have focused primarily on clinical support provided by either human clinicians or AI systems alone, with limited investigation into the possibility of collaboration between human clinicians and AI systems. The objective of this study is to evaluate the usability and physiological responses of participants to an AI-clinician support system during telemedicine emergency scenarios.

A total of 20 participants, with no medical background or prior CPR experience, were recruited. Participants were randomly assigned to (a) ChatGPT-only or (b) clinicianChatGPT collaboration groups in a balanced randomized setup.

The impact of AI-only and clinician-AI support systems on trust, acceptance, usability, and cognitive load in telemedicine scenarios was examined. Participants were randomly assigned to receive support from either an AI-only system or a clinician-AI decision support system during simulated cardiopulmonary resuscitation (CPR) scenarios in an augmented reality (AR) headset. ChatGPT 3, a widely utilized Large Language Model (LLM), was employed as the AI system. Measurements of participants' trust, acceptance, and usability were collected through questionnaires, and physiological data were gathered using a wearable wristband.

It was observed that the clinician-AI scenario was perceived as more useful compared to the AI-only scenario. Higher heart rate variability (HRV) and lower LF/HF ratios, suggesting potentially lower mental effort, were noted in the collaborative approach. However, no significant differences in system usability scale (SUS) and electrodermal activity (EDA) levels between the scenarios were found.

These findings underscore the importance of integrating clinicians in AI-supported telemedicine. Further research is recommended to explore real-world applications and validate these preliminary results. The significance of this research lies in its contribution to the existing body of knowledge on AI adoption in healthcare and its potential to inform the development of guidelines and best practices for telemedicine implementation.

This research was in collaboration with Harvard Medical School's Department of Emergency Medicine. My role on this project was to assist in data analysis and report writing. The results of this research were published at the *Cognitive and Computational Aspects of Situation Management (CogSIMA) conference* (Harari, Ahmadi, Pourfalatoun, Al-Taweel, & Shokoohi, 2024).

Chapter 8

Conclusions

This chapter provides an overall summary of the findings from this dissertation, the relevance, and dissemination of these results.

8.1 Limitations

As with most studies, there are some limitations associated with the methods used for this research. First, RQ1 and RQ2 predominately relied on self-reported [survey] data, which may be subject to social desirability and recall biases. Future research could benefit from using more objective measures, such as e-scooter usage data or observations on rider behavior. Additionally, these surveys were deployed online, hence our sample may not be representative of the broader population; as it was limited to individuals with internet access who were willing to participate in an online survey.

Moreover, all participants across all three studies resided in the state of Colorado, with RQ2 and RQ3 specifically from Fort Collins, Colorado. This is noteworthy because Colorado is a state that promotes environmentally friendly transport modes. Further research is needed to determine whether our results can be generalized to other cities with different infrastructure, regulations, or cultural norms around e-scooter use, and should seek to collect data from a more diverse and representative sample to ensure generalizability of the findings.

Similarly, RQ2 may have been limited by the duration and familiarity of shared e-scooters in Fort Collins at the time of data collection. Specifically, the scooters had only been around in the city for six months prior to the pandemic, and perhaps people had not had the chance yet to incorporate them into their travel behavior. A similar framework could be repeated in locations that have had shared mobility devices for longer.

Lastly, while RQ3 leveraged the controlled environment of a driving simulator, which provides a high degree of control over experimental variables, there are still noteworthy limitations.

The simulation setting, while highly controlled, does not completely replicate the complex visual and motion cues of real-world driving, which may influence the authenticity of observed driving behaviors. Additionally, the limited variability observed in emotional intelligence scores among participants led to non-significant results regarding its influence on driving behavior. Future studies should aim to include a broader demographic to capture a more diverse range of emotional intelligence scores. This is important, as previous literature has suggested that EI is related to driver behaviors (Ahmed & Miller, 2023; Ahmed, Ward, Otto, McMahill, & Miller, 2024; Hayley, de Ridder, Stough, Ford, & Downey, 2017).

8.2 Future Work

The study of micromobility adoption, perception, and implementation uncovers multiple potential directions for future research, thereby expanding the current scope of investigations within the field.

A valuable extension of this research would involve linking time-based weather data, such as that provided by the National Oceanic and Atmospheric Administration (NOAA), to individual micromobility trips. This approach would facilitate an examination of the effects of real-time weather conditions (e.g., precipitation, temperature, wind speed) on ridership behaviors, route choices, travel times, and safety outcomes. Insights from such studies could support infrastructure planning and policy-making by identifying weather conditions that correlate with changes in usage patterns and accident risk.

While this research utilized an emotional intelligence scale specifically designed for driving contexts, future studies could benefit from employing a general emotional intelligence scale to examine its broader impact on micromobility user behavior. This approach could offer deeper insights into how various dimensions of emotional intelligence influence decision-making, risk perception, and interactions with other road users.

By employing eye trackers in simulation studies, future research can yield insights into riders' attentional focus in diverse traffic environments. Understanding these factors could inform the development of targeted safety interventions, as well as the design of infrastructure that accommodates varying levels of rider cognitive load. The correlation between attentional focus and emotional intelligence could provide further insights on emerging vehicle technologies, such as levels of vehicle automation, as drivers tend to change their driving behaviors during and after exposure to automation (E. E. Miller & Boyle, 2019).

Future studies could also incorporate biometric data, such as heart rate variability, to assess the risk-taking behavior of micromobility users. Analyzing physiological responses in various traffic scenarios and infrastructure settings could reveal the underlying factors contributing to risky behaviors. This approach would provide objective, real-time insights into user stress and decision-making processes, beyond what self-reported data can offer. Previous research has demonstrated correlations between traffic contexts and HRV (E. E. Miller & Boyle, 2013), and adding emotional intelligence as a factor could further explain individual differences and interactions.

8.3 Research Contributions

This dissertation has thoroughly explored the complex landscape of micromobility, addressing critical questions related to user behavior, pandemic-related shifts in mobility preferences, and the psychological underpinnings of driver interactions with these vulnerable road users. The research questions provided a holistic evaluation, considering both shared and personally owned devices, [electric] bicycles, electric scooters, pedestrians, and drivers.

The detailed comparison between users and non-users of shared e-scooters (RQ1) revealed key factors influencing their choices, highlighting the importance of convenience, safety perceptions, and personal values in adopting micromobility.

The evaluation of micromobility and other shared modes before, during, and after the pandemic (RQ2) also provided novel insights. Specifically, the results showed how micromobility preferences adapted during the pandemic, demonstrating users' resilience and adaptability as mobility patterns changed with varying pandemic restrictions and safety concerns.

Furthermore, the study on the interaction between drivers and micromobility road users (RQ3) revealed that the propensity for risk-taking has a notable impact on driving behaviors, playing a key role in urban safety.

Identification of factors influencing micromobility adoption, such as perceived risk, highlights the potential effectiveness of data-driven policy interventions in crafting regulations that are tailored to users' needs. For example, introducing subsidies for helmet use, implementing speed limits in high-risk areas, or developing public awareness campaigns that highlight the environmental benefits of micromobility can address safety concerns and encourage more sustainable practices. Such data-informed policies offer a proactive means to shape rider behavior while integrating micromobility into urban transportation networks.

Operators can leverage these insights to enhance user experience through their platforms. For example, providing app-based notifications about real-time weather, safety information, and incentives for safe riding practices aligns operator goals with public safety, creating a user-centered micromobility ecosystem.

The study's findings on the adaptability of micromobility during COVID-19 pandemic, underscore its potential as a vital component of public health and emergency preparedness planning. Urban planners and public health officials can integrate micromobility into emergency response frameworks, offering a flexible, and accessible transportation alternative when traditional systems are disrupted. By complementing, rather than competing with, existing transportation systems, micromobility can enhance urban resilience and ensure continuous mobility for essential activities during future emergencies.

These findings collectively emphasize the need for a detailed understanding of user behavior, evolving preferences, and psychological factors in successfully integrating micromobility into urban landscapes. Such insights are vital for urban planning and policy-making, suggesting that a comprehensive approach that considers the complex interactions between user preferences, adaptive behaviors, and psychological factors is necessary to enhance the sustainability and safety of micromobility in urban settings.

By acknowledging the complex factors that influence user choices and behaviors, as well as the psychological aspects of driver interactions, this dissertation highlights the importance of an integrated and interdisciplinary approach to promoting a balanced coexistence of micromobility and traditional transportation modes in cities.

8.4 Publications

The results of the research questions in this dissertation have been published in two peer-reviewed journals (RQ1, RQ2), presented at one peer-reviewed conference (RQ2), with another publication still under review (RQ3). Specifically, the following output is associated with this dissertation:

- **Pourfalatoun, S.**, Gallegos, E.E., & Ahmed, J. (under review). Influence of drivers' personality factors on their interactions with bicycles and pedestrians.

- **Pourfalatoun, S.**, Ahmed, J., & Miller, E.E. (2023). Shared electric scooter users and non-users: Safety, adoption, and risk. *Sustainability, 15*(11), 9045. doi.org/10.3390/su15119045

- **Pourfalatoun, S.**, & Miller, E.E. (2023). Effects of COVID-19 pandemic on use and perception of shared e-scooters. *Transportation Research Interdisciplinary Perspectives, 22*, 100925. doi.org/10.1016/j.trip.2023.100925

- **Pourfalatoun, S.**, & Miller, E. E. (2022). Effects of COVID-19 pandemic on use and perceptions of shared micro-mobility. *Presented at the Applied Human Factors and Ergonomics (AHFE) International Conference*, New York, NY: July 2022.

Although not directly related to the topic of micromobility, the work described in Chapter 7 (Other Significant Work During PhD) resulted in two peer-reviewed journal papers, two peer-reviewed conference presentations, and one technical report. These products utilized similar research methodologies and approaches to those presented in this dissertation, and are as follows:

- Nickkar, A., **Pourfalatoun, S.**, Miller, E.E., & Lee, Y.J. (2024). Applying the heteroskedastic ordered probit model on injury severity for improved age and gender estimation. *Traffic Injury Prevention, 25*(2), pp 202-209. doi.org/10.1080/15389588.2023.2286429

- **Pourfalatoun, S.**, & Miller, E.E. (2021). User perceptions of automated truck-mounted attenuators: Implications on work zone safety. *Traffic Injury Prevention, 22*(5), pp 413-418. doi.org/10.1080/15389588.2021.1925116

- **Pourfalatoun, S.**, & Miller, E.E. (2021). Trust in automated truck-mounted attenuators: A survey on worker perceptions. *Presented at the Transportation Research Board (TRB) Annual Meeting,* TRBAM-21-02603. Washington, DC: Jan 2021.

- Miller, E.E., **Pourfalatoun, S.**, Nylen, A., & Weldon. T. (2021). *Evaluating the human-automated maintenance vehicle interaction for improved safety and facilitating long-term trust (Report No. CDOT-2021-05).* Denver, CO: Colorado Department of Transportation (CDOT). Available from: https://www.codot.gov/programs/research/pdfs/2021-research-reports/2021-05.pdf

- Harari, R. E., Ahmadi, N., **Pourfalatoun, S.**, Al-Taweel, A., & Shokoohi, H. (2024). *Clinician-AI Collaboration for Decision Support in Telemedicine: A Randomized Controlled Trial Study.* In Proceedings of Conference on Cognitive and Com (Vol. 102, pp. 81-89).

- Ebnali, M., Fathi, R., Lamb, R. L., **Pourfalatoun, S.**, & Motamedi, S. (2020, April). *Using Augmented Holographic UIs to Communicate Automation Reliability in Partially Automated Driving.* In AutomationXP@ CHI.

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Appendix A

RQ1 Survey

This appendix includes a copy of the survey questions used to collect data for RQ1 (e-scooter users vs non-users).

Introduction

The Human Systems Lab at Colorado State University is conducting research about environmental friendly and efficient mobility solutions. Your participation is voluntary, and we will only share summary results. You can stop at any time. Your responses are confidential, anonymous, and cannot be associated with your identity. Thanks for participating!

Demographics

To begin, we have a few questions about you.

We care about the quality of our survey data and hope to receive the most accurate measures of your opinions. So, it is important to us that you thoughtfully provide your best answer to each question in the survey. Do you commit to providing your thoughtful and honest answers to the questions in this survey?

- ◯ I will provide my best answers
- ◯ I will not provide my best answers

Are you a resident of the state of Colorado

- ◯ Yes
- ◯ No

What is your gender?

- ◯ Male
- ◯ Female
- ◯ Non-binary / third gender
- ◯ Prefer not to answer

What is your age?

What best describes where you live?

- Urban
- Suburban
- Rural

Which race or ethnicity best describes you?

- Asian or Pacific Islander
- Black or African American
- Hispanic or Latino
- Native American or Alaskan Native
- White or Caucasian
- Multiracial or Biracial
- Other

What is the highest level of school you have completed?

- Less than high school degree
- High school graduate (high school diploma or equivalent including GED)
- Associate degree in college (2-year)
- Bachelor's degree in college (4-year)
- Post-graduate degree (master's, doctoral, JD, MD)
- Prefer not to answer

What is your current employment status?

- Student (and employed)
- Student (not employed)
- Employed full-time
- Employed part-time
- Retired
- Not currently employed

What is your annual household income?

- Less than $35,000
- $35,000 - $49,999
- $50,000 - $74,999
- $75,000 - $99,999
- $100,000 - $149,999
- $150,000 or more

General Commute

In this section, we want to learn about your commute patterns.

Do you currently own any of the following? [check all that apply]

- ☐ Bicycle
- ☐ Electric Bicycle (e-bike)
- ☐ Electric Scooter (e-scooter)
- ☐ Personal Vehicle
- ☐ None of the above

How far is your typical commute (one direction)?

- ○ Less than one mile
- ○ 1-5 miles
- ○ 6-10 miles
- ○ 11-20 miles
- ○ More than 20 miles

How frequently do you use...

	Never	A few times a year	Monthly	Weekly	Daily
Shared Electric Scooter (e-scooter)	○	○	○	○	○
Shared Electric Bicycle	○	○	○	○	○

	Never	A few times a year	Monthly	Weekly	Daily
Bicycle	○	○	○	○	○
Personal Vehicle	○	○	○	○	○
Ride Share (Uber/Lyft)	○	○	○	○	○
Public Transit	○	○	○	○	○

Shared Electric Scooter:

In this section, we want to learn about your opinions on shared electric scooters (e-scooters).

What reasons would motivate/have motivated you to use a shared e-scooter? [check all that apply]

- ☐ To save time
- ☐ To save money
- ☐ For parking convenience
- ☐ For fun/adventure
- ☐ For environmental reasons

Which of the following trip types would you consider using shared e-scooter for? [check all that apply]

- ☐ Commuting to place of work or education
- ☐ Taking care of personal stuff (e.g. grocery, bank)
- ☐ Leisure / for fun
- ☐ Commuting from remote parking area to destination
- ☐ When exploring a new city

How often do you use a shared e-scooter as part of your journey for each of these purposes?

	Never	A few times a year	A few times a month	Weekly	Every day
Commuting to place of work or education	○	○	○	○	○
Taking care of personal stuff (e.g. grocery, bank)	○	○	○	○	○
Leisure / for fun	○	○	○	○	○
Commuting from remote parking area to destination	○	○	○	○	○
When exploring a new city	○	○	○	○	○

If a shared e-scooter was not available, which mode would you use for the following trip types...

	Walk	Bicycle	Public Transit	Drive	Ride Share (Uber/Lyft)
Commuting to place of work or education	○	○	○	○	○
Taking care of personal stuff (e.g. grocery, bank)	○	○	○	○	○
Leisure / for fun	○	○	○	○	○
Commuting from remote parking area to destination	○	○	○	○	○
When exploring a new city	○	○	○	○	○

How long is your typical journey on a shared e-scooter?

- 1-15 minutes
- 15-30 minutes
- 30-45 minutes
- 45-60 minutes
- 60+ minutes

If you were to use a shared e-scooter, how long would you like the trip to be?

- ○ Not willing to ride
- ○ 1-15 minutes
- ○ 15-30 minutes
- ○ 30-45 minutes
- ○ 45-60 minutes
- ○ 60+ minutes

Policy and Safety

How necessary do you think it is to wear a helmet while using a shared e-scooter?

- ○ Extremely unnecessary
- ○ Somewhat unnecessary
- ○ Neither necessary nor unnecessary
- ○ Somewhat necessary
- ○ Extremely necessary

How often have you experienced conflict with other road users/pedestrians while using shared e-scooters?

- Never
- Rarely
- Sometimes
- Very Often

If you were to use a shared e-scooter, how concerned would you be about experiencing conflict with other road users/pedestrians while riding?

- Not concerned at all
- Somewhat unconcerned
- Neutral
- Somewhat concerned
- Very concerned

How often do you use a helmet when riding a shared e-scooter?

- Always
- Usually
- Sometimes
- Rarely
- Never

What infrastructure changes would make you feel safer on or around e-bikes or e-scooters?

- ☐ Separated bike lanes with a physical barrier
- ☐ Smoother pavement
- ☐ Wider bike lanes
- ☐ Designated e-scooter parking
- ☐ Wider sidewalks
- ☐ No ride zones for e-scooters/e-bikes

When you ride an e-scooter/e-bike where do you tend to ride?

- ☐ On road without bike lanes
- ☐ On road but only if there are bike lanes
- ☐ Off-roads greenways and trails
- ☐ On sidewalks

How many times did you crash or nearly crash while riding a shared e-scooter?

- ○ Never
- ○ Once
- ○ Twice
- ○ Three or more times

As a pedestrian, how safe do you feel around riders on shared e-scooters?

- Very safe
- Safe
- Neither Safe nor unsafe
- Unsafe
- Very unsafe

As a driver, how safe do you feel around riders on shared e-scooters?

- Very safe
- Safe
- Neither Safe nor unsafe
- Unsafe
- Very unsafe

Bicycle vs Scooter

How safe do you feel about the following statements regarding shared e-scooters/e-bikes:

(If you have not experienced any of these statements, please select the best answer you feel is most appropriate)

	Shared Electric Scooter			Shared Electric Bicycle		
	Safe	Neutral	Unsafe	Safe	Neutral	Unsafe
You riding in vehicle lane	○	○	○	○	○	○
You riding on sidewalk	○	○	○	○	○	○
You walking and get passed by a shared rider on sidewalk	○	○	○	○	○	○
You driving and pass a shared rider in vehicle lane	○	○	○	○	○	○
Two or more people riding on the same device	○	○	○	○	○	○

	Shared Electric Scooter			Shared Electric Bicycle		
	Safe	Neutral	Unsafe	Safe	Neutral	Unsafe
Speed of the device	○	○	○	○	○	○

How agree do you feel about the following statements regarding shared e-scooters/e-bikes:
(If you have not experienced any of these statements, please select the best answer you feel is most appropriate)

	Shared Electric Scooter			Shared Electric Bicycle		
	Disagree	Neutral	Agree	Disagree	Neutral	Agree
Overall, I feel safe riding it	○	○	○	○	○	○
I am satisfied with its sanitary level	○	○	○	○	○	○
I feel comfortable riding it	○	○	○	○	○	○
If I am drunk, I would feel comfortable riding it	○	○	○	○	○	○
It is a good choice while shopping/grocery	○	○	○	○	○	○
I am satisfied with its design/usability	○	○	○	○	○	○

	Shared Electric Scooter			Shared Electric Bicycle		
	Disagree	Neutral	Agree	Disagree	Neutral	Agree
I need dedicated lanes to ride	○	○	○	○	○	○

What is your main reason for not using shared e-scooters?

What is the main reason for not using shared e-bicycles?

Personality Questions:

Please indicate the extent to which you agree or disagree with the following statements. Please do not think too long before answering; usually your first inclination is also the best one.

	Strongly disagree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Strongly agree
Taking risks makes life more fun	○	○	○	○	○
My friends would say that I'm a risk taker	○	○	○	○	○
I enjoy taking risks in most aspects of my life	○	○	○	○	○
I would take a risk even if it meant I might get hurt	○	○	○	○	○
Taking risks is an important part of my life	○	○	○	○	○
I commonly make risky decisions	○	○	○	○	○
I am a believer of taking chances	○	○	○	○	○
I am attracted, rather than scared, by risk	○	○	○	○	○

What best describes you when it comes to technology?

- ○ I am skeptical of new technologies and use them only when I have to.
- ○ I am usually one of the last people I know to use new technologies.
- ○ I usually use new technologies when most people I know do.
- ○ I like new technologies and use them before most people I know.

○ I love new technologies and am among the first to experiment with and use them.

Appendix B

RQ2 Survey

This appendix includes a copy of the survey questions used to collect data for RQ2 (COVID-19 impacts).

Colorado State University

General Commute

Do you currently own any of the following? [check all that apply]

- ☐ Bicycle
- ☐ Electric Bicycle
- ☐ Electric Scooter (e-scooter)
- ☐ Personal Vehicle

How far is your typical comumute?

- ○ Less than one mile
- ○ 1-5 miles
- ○ 6-10 miles
- ○ more than 10 miles

How frequently do you use...

	Never	A few times a year	Several times a month	Weekly	Daily
Electric Scooter	○	○	○	○	○
Bicycle	○	○	○	○	○
Personal Vehicle	○	○	○	○	○
Ride Share (Uber/Lyft)	○	○	○	○	○
Public Transit	○	○	○	○	○

How important are each of the following factors in your transportation mode choice?

	Not at all important	Slightly important	Moderately important	Very important	Extremely important
Distance	○	○	○	○	○
Avoiding traffic	○	○	○	○	○
Parking	○	○	○	○	○
Weather	○	○	○	○	○

	Not at all important	Slightly important	Moderately important	Very important	Extremely important
Environmental impact	○	○	○	○	○

Which of the following trip types would you consider using an electric scooter for? [check all that apply]

- ☐ To/From work
- ☐ To/From school
- ☐ To/From shopping
- ☐ To/From socializing (with family/friends)
- ☐ To/From sporting/concert events
- ☐ To/From remote parking area to destination

If an electric scooter was not available, which mode would you use for the following trip types...

	Walk	Bicycle	Public Transit	Drive	Ride Share (Uber/Lyft)
To/From work	○	○	○	○	○
To/From school	○	○	○	○	○
To/From shopping	○	○	○	○	○
To/From socializing (with family/friends)	○	○	○	○	○
To/From sporting/convert events	○	○	○	○	○
To/From remote parking area to destination	○	○	○	○	○

Bicycle vs Scooter

What is your experience with shared electric scooters? [check all that apply]

- ☐ I have ridden one at least once in Fort Collins
- ☐ I have ridden one at least once in another city
- ☐ I have seen people ride them
- ☐ I have no experience with shared electric scooters

What is your experience with shared bicycles? [check all that apply]

- ☐ I have ridden one at least once in Fort Collins
- ☐ I have ridden one at least once in another city

- ☐ I have seen people ride them
- ☐ I have no experience with shared bicycles

How safe do you feel about the following regarding electric scooters?

	Extremely unsafe	Unsafe	Neutral	Safe	Extremely safe
You riding in vehicle lane	○	○	○	○	○
You riding on sidewalk	○	○	○	○	○
Others riding on sidewalk	○	○	○	○	○

How safe do you feel about the following regarding bicycles?

	Extremely unsafe	Unsafe	Neutral	Safe	Extremely safe
You riding in vehicle lane	○	○	○	○	○
You riding on sidewalk	○	○	○	○	○
Others riding on sidewalk	○	○	○	○	○

How would you rate shared electric scooters in terms of...

Unsafe	○	○	○	Safe
Unsanitary	○	○	○	Sanitary
Uncomfortable	○	○	○	Comfortable
Cost in-effective	○	○	○	Cost effective
Hard to ride	○	○	○	Easy to ride
Hard to find parking	○	○	○	Easy to find parking

How would you rate shared bicycles in terms of...

Unsafe	○	○	○	Safe
Unsanitary	○	○	○	Sanitary
Uncomfortable	○	○	○	Comfortable
Cost in-effective	○	○	○	Cost effective
Hard to ride	○	○	○	Easy to ride
Hard to find parking	○	○	○	Easy to find parking

How strongly do you agree with the following statements about electric scooters?

	Strongly disagree	Somewhat disagree	Neutral	Somewhat agree	Strongly agree
They have enough cargo space	○	○	○	○	○

	Strongly disagree	Somewhat disagree	Neutral	Somewhat agree	Strongly agree
They are good exercise	O	O	O	O	O
I am worried I will get hit	O	O	O	O	O
I am worried I will hit someone	O	O	O	O	O
I am worried about running out of battery	O	O	O	O	O

How strongly do you agree with the following statements about bicycles?

	Strongly disagree	Somewhat disagree	Neutral	Somewhat agree	Strongly agree
They have enough cargo space	O	O	O	O	O
They are good exercise	O	O	O	O	O
I am worried I will get hit	O	O	O	O	O
I am worried I will hit someone	O	O	O	O	O

COVID Pandemic

Which best describes your quarantine status over the past 6 months?

- O Full isolation, not leaving my home at all
- O Stayed home, only leaving for essential activity
- O Stayed home, only leaving for essential activity and work
- O Left my house similar to before pandemic

How likely would you be to use a shared bicycle/scooter...

	Extremely unlikely	Somewhat unlikely	Neutral	Somewhat likely	Extremely likely
Before COVID19 pandemic	O	O	O	O	O
During COVID19 pandemic	O	O	O	O	O
After COVID19 pandemic	O	O	O	O	O

How likely would you be to use public transit...

	Extremely unlikely	Somewhat unlikely	Neutral	Somewhat likely	Extremely likely
Before COVID19 pandemic	O	O	O	O	O

	Extremely unlikely	Somewhat unlikely	Neutral	Somewhat likely	Extremely likely
During COVID19 pandemic	O	O	O	O	O
After COVID19 pandemic	O	O	O	O	O

How likely would you be to use ride share (Uber/Lyft)...

	Extremely unlikely	Somewhat unlikely	Neutral	Somewhat likely	Extremely likely
Before COVID19 pandemic	O	O	O	O	O
During COVID19 pandemic	O	O	O	O	O
After COVID19 pandemic	O	O	O	O	O

Demographics

What is your age?

What is your gender?

- Male
- Female
- Other
- Prefer not to answer

What is your race/ethnicity?

- Asian or Pacific Islander
- Black or African American
- Hispanic or Latino
- Native American or Alaskan Native
- White or Caucasian
- Multiracial or Biracial
- Other

What is the highest level of education you have completed?

- Some High School

- High School Diploma
- Some College
- Associates Degree
- Bachelor's Degree
- Postgraduate Degree

What is your current employment status?

- Student
- Employed full-time
- Employed part-time
- Retired
- Not currently employed

What is your annual household income?

- Less than $35,000
- $35,000 - $49,999
- $50,000 - $74,999
- $75,000 - $99,999
- $100,000 - $149,999
- $150,000 or more

Have you mostly lived in Fort Collins over the past 6 months?

- Yes
- No

Appendix C

RQ3 Survey

This appendix includes a copy of the survey questions used to collect data for RQ3 (Drivers' Personality Factors on Interactions).

Student ID

Participant Number: (to be filled out by researcher)

DEIS

First, we want to ask you some questions about driving...

How strongly do you agree/disagree with the following statements:

	Strongly disagree	Disagree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Agree	Strongly agree
I often find it difficult to adjust my driving to traffic and driving conditions.	○	○	○	○	○	○	○

	Strongly disagree	Disagree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Agree	Strongly agree
I often find it difficult to care about other road users on the road with me.	○	○	○	○	○	○	○
I tend to get involved in driving situations that I wish I could have avoided.	○	○	○	○	○	○	○
I understand my strengths and weaknesses as a driver very well.	○	○	○	○	○	○	○
I'm usually able to see things from another road user's perspective.	○	○	○	○	○	○	○
I'm usually able to influence the behavior and feelings of other road users.	○	○	○	○	○	○	○
I often think about my feelings while driving.	○	○	○	○	○	○	○

	Strongly disagree	Disagree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Agree	Strongly agree
I usually find it difficult to regulate my emotions while driving.	◯	◯	◯	◯	◯	◯	◯

	Strongly disagree	Disagree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Agree	Strongly agree
I generally believe that I am safe when I drive.	◯	◯	◯	◯	◯	◯	◯
Many times, I can't figure out what emotion I'm feeling while driving.	◯	◯	◯	◯	◯	◯	◯
Generally, I'm able to adapt to different traffic and driving situations.	◯	◯	◯	◯	◯	◯	◯
I worry that other drivers get upset with me.	◯	◯	◯	◯	◯	◯	◯
Overall, I have a gloomy feeling about driving.	◯	◯	◯	◯	◯	◯	◯

	Strongly disagree	Disagree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Agree	Strongly agree
I'm usually able to find ways to control my emotions while driving.	○	○	○	○	○	○	○
I feel that I have a number of good driving qualities.	○	○	○	○	○	○	○
I normally find it difficult to stay focused as a driver.	○	○	○	○	○	○	○

	Strongly disagree	Disagree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Agree	Strongly agree
I cooperate effectively with other drivers.	○	○	○	○	○	○	○
Others would describe me as an anxious driver.	○	○	○	○	○	○	○
I often find it difficult to assert myself in traffic.	○	○	○	○	○	○	○

	Strongly disagree	Disagree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Agree	Strongly agree
I tend to change my mind frequently while driving.	○	○	○	○	○	○	○
I generally don't find driving enjoyable.	○	○	○	○	○	○	○
Managing my emotions while driving is not a problem for me.	○	○	○	○	○	○	○
People who drive with me often complain that I don't treat other drivers right.	○	○	○	○	○	○	○
I often find it difficult to see things from another driver's viewpoint.	○	○	○	○	○	○	○
	Strongly disagree	Disagree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Agree	Strongly agree

	Strongly disagree	Disagree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Agree	Strongly agree
I find it difficult to think that other road users are similar to me.	○	○	○	○	○	○	○
I would describe myself as good at resolving conflict with other road users.	○	○	○	○	○	○	○
Overall, I'm highly motivated to be a safe and courteous driver.	○	○	○	○	○	○	○
I tend to get intimidated by stressful driving situations.	○	○	○	○	○	○	○
Overall I'm able to deal with driving-related stress.	○	○	○	○	○	○	○
Overall, I'm pleased with my driving.	○	○	○	○	○	○	○

drive cue

Thank you. You will now complete a practice drive followed by the study drive in the driving simulator.

Demographics

We have a few questions about you...

What is your gender?

- ○ Male
- ○ Female
- ○ Other / Prefer not to answer

How old are you?

What is the highest level of school you have completed?

- Less than high school degree
- High school graduate (high school diploma or GED)
- Some college but no degree
- Bachelor's degree in college (4-year)
- Post-graduate degree (master's, doctoral, JD, MD)
- I prefer not to answer

How many years have you had a drivers license for?

How strongly do you agree/disagree with the following statements. Please do not think too long before answering; usually your first inclination is also the best one.

	Strongly disagree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Strongly agree
Taking risks makes life more fun	○	○	○	○	○

	Strongly disagree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Strongly agree
My friends would say that I'm a risk taker	○	○	○	○	○
I enjoy taking risks in most aspects of my life	○	○	○	○	○
I would take a risk even if it meant I might get hurt	○	○	○	○	○
Taking risks is an important part of my life	○	○	○	○	○
I commonly make risky decisions	○	○	○	○	○
I am a believer of taking chances	○	○	○	○	○
I am attracted, rather than scared, by risk	○	○	○	○	○

Micromobility

Next, we have a few questions about your typical driving experiences...

How frequently do you use a...

	Never	A few times a year	A few times a month	Weekly	Daily
Electric Scooter (e-scooter)	○	○	○	○	○
Bicycle	○	○	○	○	○
Personal Vehicle	○	○	○	○	○

As a driver, how comfortable do you feel while passing a bicyclist/scooter...

	Extremely uncomfortable	Uncomfortable	Neutral	Comfortable	Extremely comfortable
On the road (sharing the lane)	○	○	○	○	○
In the bike lane	○	○	○	○	○
On the sidewalk	○	○	○	○	○

How strongly do you agree with the following statements: As a driver, I would...

	Strongly disagree	Somewhat disagree	Neutral	Somewhat agree	Strongly agree
Slow down passing a bicycle on the sidewalk	○	○	○	○	○
Slow down passing a bicycle in the bike lane	○	○	○	○	○
Slow down passing a bicycle on the road	○	○	○	○	○
Give extra lateral space when passing a bicycle in the bike lane	○	○	○	○	○
Give extra lateral space when passing a bicycle on the road	○	○	○	○	○