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Modeling the Perceived Mental and Physical Wellness Impacts of Shared Micromobility Trips

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Modeling the Perceived Mental and Physical Wellness Impacts of Shared Micromobility Trips

By

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Abstract

Shared micromobility use has the potential to improve physical and mental wellness. As bike share and scooter share systems become more popular and the effects of their use more understood, it is important to consider how users perceive these systems to be affecting them. How users perceive the effects of riding shared micromobility may influence how much they choose to ride, and their riding experiences may in turn shape those perceptions. Additionally, how safe users feel when using bike share and scooter share is important in evaluating if the built environment is adequately serving these users as changes in design are made over time to better accommodate walking, bicycling, and scooting in cities. Active travel modes like bicycling also provide a healthier alternative to driving, and it is useful to know if users of bike share and scooter share feel they are experiencing more physical activity as a result of their use of micromobility.

Therefore, in this dissertation I include three studies to model the perceived mental and physical wellness impacts of shared micromobility trips. I leverage the survey and travel diary data from the American Micromobility Panel (AMP) project, which surveyed bike share and scooter share users in the United States in summer of 2022. The AMP project recruited participants from five major shared micromobility operators across 48 cities in the United States. Participants completed a travel diary during the study period, which tracked the trips they made and allowed participants to describe their trips, such as by mode used to complete the trip. Following the travel diary, participants were invited to complete a survey which asked them various questions about their experiences using shared micromobility. This pairing of the travel diary and the survey allowed for me to associate each participant's experience riding bike share

or scooter share (such as the weather during the trips) with their responses about their overall experiences and perceptions of shared micromobility and their well-being.

The first study modeled users' perceived changes in their mental wellness as a result of shared micromobility use. Participants were asked how much they agree or disagree that riding a bike share bike/scooter share scooter improves their mental health. They were also asked if after riding a bike share bike/scooter share scooter, they feel less stressed than before their trip. Finally, participants responded with how much they agree or disagree that they feel relaxed while riding a bike share bike/scooter share scooter. I used these three questions to describe a participant's perceived mental wellness. I concluded that introducing bike share use to one's daily routine can positively impact their perceived mental wellness for that first trip or two on average, with diminishing returns with increased riding. However, scooter share is not expected to influence a person's perceived mental wellness.

The second study modeled users' perceived safety of shared micromobility based on their level of agreement or disagreement that bike share/scooter share is unsafe and that they worry about crashing bike share/scooter share. The model predicts that participants are more likely to find bike share safer than scooter share and shows that a user's perceived experiences almost crashing their bike share bike or scooter share scooter is a useful indicator in predicting their perceived safety of shared micromobility. Unlike with perceived mental wellness, the amount of daily shared micromobility use on average does not indicate how safe they perceive shared micromobility to be.

The final study modeled users' perceived changes in physical activity as a result of their shared micromobility use. Participants were asked how much their use of micromobility changed how much they walk, bike, and scoot. According to the model results, users are predicted to be more likely to agree that they increase their physical activity (via walking, biking, or scooting) as they increase their scooter share use in minutes per day on average. This increase in perceived change in physical activity is predicted to be strongest for those first 10 minutes per day of scooter share use, and bike share use is not expected to have any strong effect on this perceived change in physical activity.

We can expect positive perceived changes in mental wellness, safety, and physical activity as a result of one's experiences with shared micromobility according to the results of my three models. The uncertainty in the results suggest a need for further exploring the important pathways for improving a person's perceptions of mental and physical wellness. Based on the results of the models, individual characteristics appear to be much more important predictors of wellness than city-level characteristics or the aggregate experiences of the weather and built environments during the micromobility trips. However, the sociodemographic characteristics included in the model were not as important as the perceived experiences of using shared micromobility.

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1 Introduction

1.1 Dissertation Overview

Shared micromobility use has the potential to improve physical and mental wellness. As bike share and scooter share systems become more popular and the effects of their use more understood, it is important to consider how users perceive these systems to be affecting them. How users perceive the effects of riding shared micromobility may influence how much they choose to ride, and their riding experiences may in turn shape those perceptions. Additionally, how safe users feel when using bike share and scooter share is important in evaluating if the built environment is adequately serving these users as changes in design are made over time to better accommodate walking, bicycling, and scooting in cities. Active travel modes like bicycling provide a healthier alternative to driving, and it is useful to know if users of bike share and scooter share feel they are experiencing more physical activity as a result of their use of micromobility.

Therefore, in this dissertation I include three studies to model the perceived mental and physical wellness impacts of shared micromobility trips. The first study modeled users' perceived changes in their mental wellness as a result of shared micromobility use. Mental wellness is defined by three dimensions: mental health, stress, and feeling relaxed. The second study modeled users' perceived safety of shared micromobility based on two dimensions of safety: perceiving bike share or scooter share to be unsafe and worrying about crashing. The final study modeled users' perceived changes in physical activity as a result of their shared micromobility use. Perceived change in physical activity was captured with the following three dimensions: perceived changes in walking, biking, and scooting. I leverage the survey and travel diary data from the American Micromobility Panel (AMP) project, which surveyed bike share and scooter share users across 48 cities in the United States in summer of 2022. Participants completed a travel diary during the study period to describe the trips they made, which were tracked by a smartphone application. Following the travel diary, participants were invited to complete a survey which asked them various questions about their experiences using shared micromobility. This pairing of the travel diary and the post-diary survey allowed me to associate each participant's experience riding bike share or scooter share with their perceptions of shared micromobility and their well-being.

1.2 Shared Micromobility

Shared micromobility is a mobility service in which a user may rent a bicycle, electric bicycle (e-bike), or electric scooter (e-scooter) for use freely within a predefined geographic boundary or between docking stations for the vehicles. Users may use their smartphones to access applications (apps) developed by the service operators to view the available vehicles or docking stations near them, reserve a vehicle, and pay for their rental. Shared micromobility began with the introduction of shared bikes in Amsterdam, Netherlands, in 1965 as a collection of uniform and easily identifiable bicycles distributed throughout the city and left unlocked with the intent that people would use these bikes freely and reduce their driving. This style of micromobility often failed due to theft of the bicycles, but it persisted until the 1990s when coin deposit systems emerged (Shaheen et al., 2010). In these systems, the number of bicycles was much greater, and the bicycles had to be accessed from docking stations where a coin deposit unlocked the bicycle for use. Advancements in technology have allowed for theft prevention with IT-based systems that include some form of user interface, smart technology, and membership services (Shaheen et al., 2010).

Shared micromobility has since evolved over the recent decade to utilize the data that these smart devices are now able to collect to improve the service, such as rebalancing the distribution of devices based on patterns of demand or integrating with local public transit systems (Shaheen et al., 2010). Recent technology and data collection has also enabled research into user behavior that was not possible before, such as aiding the rebalancing of a bike share system with incentives that guide a user's selection of a bike (Fukushige et al., 2022). Systems have become multimodal, incorporating traditional bicycles and new micromobility options such as e-bikes and e-scooters. E-scooters have emerged as a regular fixture of shared micromobility services, and they have proven to be a viable and competitive addition to the list of micromobility modes that are used for last-mile trips (Baek et al., 2021), used for recreational trips more than commute trips (Caspi et al., 2020), and are less sensitive to weather conditions than bike share trips (Noland, 2021). Shared micromobility services are likely here to stay as they have proven to be resilient through the COVID-19 pandemic (H. Wang and Noland, 2021), and they are a useful instrument in reducing vehicle miles traveled (VMT) (M. Wang and Zhou, 2017) as cities pursue a more sustainable and equitable transportation future.

1.3 Shared Micromobility Travel Behavior

The introduction of shared micromobility in cities has been shown to influence travel behavior more broadly, such as bike share systems reducing urban rush hour VMT (M. Wang and Zhou, 2017). The VMT reduction attributable to e-scooters may have been underestimated by academics and public agencies relying on methods using shares of trips rather than shares of distance traveled on e-scooters (Meroux et al., 2022), but research into how to best quantify the VMT reduction is still relatively new (Meroux et al., 2022). Shared e-scooters may also compete with ride hailing and taxis (Guo and Zhang, 2021) in addition to their potential for replacing trips in a personal vehicle. Guo and Zhang (2021) also concluded that more exposure to e-scooters as a mode of travel, private or shared, can increase the chances of people using shared e-scooters, which demonstrates a potential for more e-scooter trips replacing driving trips in the future with increased availability of e-scooters.

Recent research has examined how satisfaction with one's travel influences the willingness to try or continue to use shared micromobility. Studies have found that satisfaction with one's current travel not only results from travel experiences but can also influence whether individuals try shared micromobility as an alternative to their existing mode or adjust how often they use it (Guan et al., 2024). Bike share users are more satisfied with using bike share than they are riding a personal bicycle, and they also prefer to use bike share as their commute mode more than as a connection for other modes (Z. Chen et al., 2022). These results highlight the importance of travel mode satisfaction on travel behavior as it relates to shared micromobility, and the continued or increased use of shared micromobility.

Although the literature on shared micromobility is growing rapidly, it remains limited. However, much can be learned from the bicycle literature that is likely applicable to shared micromobility, such as how and where users are more likely to use these modes. Bicyclists have been shown to make their trips primarily on network links with dedicated bicycling infrastructure (Dill, 2009). Fitch and Handy (2020) showed a preference by bicyclists for protected infrastructure or separate paths and to avoid steep slopes, while overall e-scooter users and bicyclists have been observed to have similar infrastructure preferences (Zhang et al., 2021). These infrastructure preferences may also help determine if a bicyclist will choose to bike for their trip (Winters et al., 2011). Bike share use has been shown to increase with the introduction of safer infrastructure for bicycling (Van Veghel and Scott, 2024). These findings emphasize the importance of expanding the network of dedicated, protected infrastructure within North American cities to influence the use of shared micromobility.

For bicycling, it has been shown that sociodemographic characteristics affect bicycle trip characteristics (Misra and Watkins, 2018). The travel behavior of bicyclists may be governed by their perceptions of the built environment as well. Research has shown that for bicyclists, imagined safety of a roadway has a negative bias compared to safety opinions after real experiences riding on the roadways (Fitch and Handy, 2018). Ma and Dill (2015) determined that bicycling frequency is influenced by perceptions of the environment, and they recommend that researchers incorporate both perceptions and objective measures when researching bicycling. Both studies highlight the importance of gauging a micromobility user's opinion on the safety of their trip as they make them as well as identifying the types of infrastructure they used and how it might influence their safety opinions.

The use of active travel modes may be influenced by the amount of use of these modes in an area as well as the characteristics of the area. Heydari et al. (2022) found that, in London, U.K., the levels of walking and bicycling were more important in determining scooter safety than traffic volumes at the borough scale but note that these results may change at a street-level analysis. They also found that safety increased with a higher prevalence of greenspaces, and neighborhoods with higher proportion of minority residents, more schools, or more crime are at higher risks of more scooter crashes.

Existing research documents a variety of benefits generated by micromobility because of changes in travel behavior. Bike share may reduce traffic congestion (Hamilton and Wichman, 2018) and provide greater accessibility to disadvantaged communities (Qian and Jaller, 2021). Replacing sedentary trips with active travel also increases physical activity, which has positive health benefits physically and mentally (Abduljabbar et al., 2021). However, the existing literature shows gaps in our understanding of the health impacts of shared micromobility use limiting our ability to draw conclusions for crafting policy. To address that gap, this dissertation uses a health lens to look at the outcomes of micromobility use within cities in the United States.

1.4 Health Outcomes

Micromobility has the potential to improve physical and mental health. Micromobility is a form of active transportation and physical activity. Incorporating regular physical activity reduces one's risk of cardiovascular diseases and obesity, and it also improves mental health (Warburton et al., 2006). Yet, physical health also encompasses a person's safety, and traffic safety is a primary concern. Traffic crashes result in about 1.19 million deaths globally each year, more than half of which involve people outside of a passenger vehicle. Traffic violence is so prevalent that it is the leading cause of death for those 5-29 years (World Health Organization, 2023), and this is also true for teenagers in the United States (U.S. Department of Transportation, 2023). Traffic fatalities in the United States remain a challenge to overcome with 40,990 people dying in 2023 alone (U.S. Department of Transportation, 2023). Roadways in the United States have become especially unsafe for pedestrians with 7,314 deaths in 2023 (U.S. Department of Transportation, 2025).

These traffic safety risks also extend to micromobility. A study of emergency departments in Southern California found that users of e-scooters were less likely to be wearing a helmet, and head injuries were common. They also found that many injuries were by underage users (Trivedi et al., 2019). Similarly, a literature review of bike share injuries and helmet use found that users of bike share systems were less likely to be wearing helmets than riders of privately owned bicycles (S. Chen et al., 2021). However, helmet use is not the only factor to consider for the safety of micromobility use. DiGioia et al. (2017) conducted a literature review of the infrastructure impacts on bicycle safety and found that bicycle lanes in general are beneficial for the safety of bicyclists and may reduce collisions, and more multimodal infrastructure treatments like bicycle boulevards and bicycle tracks can reduce crash rates. Despite recent increases in research on the topic, the authors note there are still significant gaps in the literature in characterizing the safety improvements of infrastructure treatments for bicyclists. For example, Vanparijs et al. (2015) identified that research into bicycle safety may lack measures of exposure, although the effectiveness of safety treatments is measurable. Attitudes towards safety of bicycling has an impact on whether a person will continue to bicycle. Lee et al. (2015) interviewed adults in Davis, California, a city known for its significant bicycling mode share, about their experiences throughout their lives with bicycling. Crashes or incidents with motor vehicles, especially in adulthood, had a negative impact on the participants' attitudes and willingness to bicycle. That said, incidents during childhood and incidents that are solo or accidents while riding were less likely to negatively impact attitudes. This suggests that near-misses or crashes with other non-motorized traffic may have less impact on their attitudes than near-misses or crashes with motor vehicles.

Micromobility use in urban areas also exposes users to emissions from heavy traffic. An extensive literature review concluded that bicyclists are more exposed to these emissions than riders of passenger vehicles (Gelb and Apparicio, 2021). As vehicle volumes increase along a roadway, exposure to emissions can be expected to be increased. Gelb and Apparicio (2021) also found after reviewing health research, that the benefits from active travel may outweigh the health effects of pollution exposure. Anowar et al. (2017) found that bicyclists are willing to detour from the shortest path to their destination for a route with less air pollution exposure if the new route is within four minutes of their original travel time, suggesting that bicyclists are still sensitive to their exposure to pollution and will strive to mitigate it.

Micromobility health outcomes from physical activity may vary among users. The introduction of micromobility systems like docked bike share favored wealthier areas in New York City even as the system expanded, although the health benefits were found to be promising (Babagoli et al., 2019). Inequity in micromobility benefits is reflective of active transportation more broadly. Qian and Wu (2019) note that despite bike share providing health benefits when replacing a trip by automobile, many disadvantaged communities face increased air pollution burdens compared to other communities when studying bike share trip routes. Considering active transportation, Barajas and Braun (2021) identified fewer reported health benefits for participants of color for biking and walking, and these disparities in health benefits may extend to mental health in addition to physical health. Additionally, access to safer bicycle infrastructure for active transportation users is not equal for all users, which is necessary for both general active transportation and for micromobility use. Braun et al. (2019) showed that there are disparities in access to bicycle lanes at the census block group level based on resident characteristics, such as race, ethnicity, and socioeconomic status. This included determining whether the census block group had bicycle lanes, the bicycle lane connectivity, and the proximity to the nearest bicycle lanes outside of the census block group. Overall, this measure of bicycle lane access was more associated with higher education and less associated with block groups with larger populations of Hispanic residents. Braun et al. (2021) found associations between bicycling risks, in the form of air pollution exposure and risks of injury and fatality, and sociodemographic characteristics of census block groups within Los Angeles, California. Generally, communities with higher median incomes have substantially less risk of crashing on a bicycle based off a crash risk measure incorporating bicycle crash incident data and bicycling activity (which was extrapolated from counts of bicycle volumes). Also, communities with a higher proportion of White residents have less health risks than those with more Hispanic or non-White residents. While existing research has focused on the types of injuries sustained by users of micromobility (Fang, 2022; Yang et al., 2020), there has been less of an emphasis on understanding disparities in safety risks and physical health benefits for users of micromobility specifically.

Nonetheless, the benefits to using micromobility can improve a user's physical health and mental health. Hou et al. (2022) found that in New York, New York, the bike share system Citi Bike has provided an overall public health benefit of over 5,700 Disability Adjusted Life Years (DALYs) compared with a hypothetical scenario in which Citi Bike were not to exist. These health benefits can also extend to mental health in addition to physical health. Increasing utilitarian bicycling, such as for commuting, is associated with less psychological distress, greater life satisfaction (Ma and Ye, 2022), reduced stress (Avila-Palencia et al., 2017; Sattler et al., 2020), and an improved perceived work-life balance (Herman and Larouche, 2021). Generally, active transportation like bicycling and walking positively influences a person's commute well-being (Smith, 2017; Singleton, 2019). Grant-Muller et al. (2023) found that shared e-scooter use improved users' stress generally, suggesting that riding a shared e-scooter may provide similar benefits as bike share or walking.

Mueller et al. (2015) performed a literature review of 30 studies regarding the net health impacts of active transportation, such as walking and biking, and found that overall, the health benefits of the increased physical activity from active transportation outweighs any health risks active transportation might pose, such as increased exposure to vehicle emissions or conflicts with motor vehicles. Gotschi (2011) showed that as Portland, Oregon, expanded their network for bicyclists, bicycling increased and the rates of crashes and fatalities decreased. Researchers support advocating for increased bicycling because the benefits of a healthy, active lifestyle outweigh any risks of injury while bicycling (Götschi, 2016). However, the pattern of net positive health benefits with walking and bicycling might not hold for riding a scooter. Wen et al. (2025) measured more physical activity from riding an e-scooter than for driving but riding an e-scooter provided less physical activity than walking. There is evidence that scooter trips replace walking trips (Wang et al., 2023). Sanders et al. (2022) found that e-scooter trips were largely replacing walking trips and reducing the potential physical activity otherwise experienced by a small sample of users in Phoenix, Arizona. They also measured e-scooter trips to be similar to trips in a personal vehicle with regards to physical activity. These findings underscore that the health impacts of shared micromobility depend on travel behavior, as well as the safety risks.

Less is known about how shared micromobility travel behavior translates to health outcomes. Bigazzi et al. (2022) conducted an extensive literature review on the state of research on the perceptions of safety and comfort by active transportation travelers. They identified environmental characteristics and routing as key factors for inducing or mitigating stress and suggested that more studies are needed into factors that positively affect stress levels by travelers. There is also a need for more research into the predictors of health outcomes for shared micromobility, which is a motivation for this research.

1.5 Measurement of Key Predictors of Health Outcomes

Studies have measured health outcomes of micromobility in a variety of ways, including by capturing physiological or biometric indicators of stress and exertion. Teixeira et al. (2020) used biometrics to measure stress, and they found that the built environment affects the stress of bicyclists, although the degree can vary by study location. Fitch et al. (2020) used heart rate variability (HRV) measurements and survey questions of participants while bicycling with wearable technology to characterize the stress felt while bicycling on different street segments. However, this study was limited in scope and number of participants, as equipping the student participants with the biometric sensors required preparation and limited the possible bicycling routes and total distance.

When the limitations of biometric measurements are difficult or impossible to overcome for a study, surveys are a popular alternative to measuring a variety of health outcomes. The International Physical Activity Questionnaire (IPAQ) is one such survey method to measure physical activity that adults experience throughout their day (Craig et al., 2003). Researchers used surveys to understand perceptions of the safety of e-scooter use (Pourfalatoun et al., 2023) and the impact of stress as a result of using e-scooters (Grant-Muller et al., 2023), among many others. Surveys allow for a greater scope than using biometrics, but they also have unique drawbacks that should be considered. A comprehensive review of validation studies of the use of the International Physical Activity Questionnaire – Short Form (IPAQ-SF) in research revealed that IPAQ-SF overestimates the amount of average physical activity by an average of 84% (Lee et al., 2011). Surveys are also a useful way to collect data about predictors as well as other outcomes of micromobility use. Hoehner et al. (2005) surveyed adults in both a more-walkable and less-walkable city to compare their perceived physical activity with their surrounding built environments. Nikiforiadis et al. (2024) measured e-scooter user satisfaction with surveys in Greece. When it comes to measuring the perceived health outcomes of using shared micromobility, surveys are a practical tool offering insight into how users' perceptions of health may be shaped by their travel experiences.

Beyond the health benefits of increased physical activity and potential VMT reduction, the experience of using shared micromobility can also result in mental health related outcomes. Wild and Woodward (2019) found that bicyclists are the most satisfied with their commutes to work because traveling by bicycle allows them more social interaction with their community, among other factors. Bicyclists likely have a higher sense of satisfaction with their commutes because of the increased physical activity and potential for social interaction with other bicyclists (Wild and Woodward, 2019), which is one aspect of mental health, satisfaction, or pleasure that may be key in counteracting other detrimental effects of bicycling. Detrimental effects researchers have identified include increased stress due to interactions with motor vehicles, the quality of the pavement and infrastructure, or the speed differential between motor vehicles and bicyclists (Gadsby et al., 2021). Researchers have identified that streets like local roads with lower speeds and lower traffic volumes where bicycles can exert their priority in traffic are less stressful for bicyclists than larger, high-volume streets (Fitch et al., 2020). Aman et al. (2021) analyzed over 12,000 e-scooter share service rider reviews to evaluate user satisfaction and to determine what influences a rider's willingness to use the service and their level of comfort, finding that rider satisfaction varies across demographics like gender. The researchers also suggest that public policies incorporate user opinions to improve rider satisfaction, which can promote an increase in micromobility use. These findings suggest that some health outcomes of using shared micromobility are not universally experienced, and instead could vary by user demographic, the purpose of the trip, or the environment the trip was made in, making these important measures to effectively study the health outcomes of shared micromobility use.

1.6 Research Goals

This research aims to address limitations in our understanding of how the use of shared micromobility affects a user's perceived mental and physical health by linking the environmental conditions of traveling, such as the built environment, to health outcomes. My three studies contribute to the existing research by modeling 1. perceived changes in mental wellness, 2. perceived safety of shared micromobility, and 3. perceived changes in physical activity with users' shared micromobility use, aspects of their trips, and their individual characteristics. These studies are made possible by the following methodological contributions utilizing the unique AMP project data:

1. My studies include the GPS traces of trips taken by users for a more accurate representation of the health burdens on users of shared micromobility in the form of bike share and scooter share. The data from the AMP project has an advantage over data used in prior micromobility research, where they did not have access to the locations of the devices throughout the trip. Qian and Wu (2019), for example, relied on a Google Direction API to generate likely routes between origin-destination pairs of trips.
2. My studies expand on prior research (e.g., Willis et al., 2013) by linking route-level information with survey responses and broader built environment contexts across the United States. This addresses challenges identified in earlier studies: for example, Willis et al. (2013) analyzed bicycling satisfaction with survey data without information about their routes and was confined to a university. Similarly, Sanders et al. (2022) focused only on a few locations, limiting the generalizability of their findings.

Together, these contributions provide a framework for a better understanding of how shared micromobility use can influence perceptions of mental and physical wellness impacts of riding shared micromobility.

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2 Methodology

2.1 The American Micromobility Panel Project

I evaluated the mental health, safety, and physical health impacts of shared micromobility using a survey and travel diary data from shared micromobility users across various cities in the United States. The data were collected during Summer 2022 as part of the American Micromobility Panel (AMP) project (Fitch et al., 2023).

The AMP project was conducted during Summer 2022. Shared micromobility users were recruited across 48 cities in the United States, as shown in Figure 2.1. Recruitment and data collection was the result of a partnership between five shared micromobility operators (Bird, Lime, Lyft, Spin, and Superpedestrian) and Resource Systems Group (RSG). Participants were bike-share or scooter-share users who opted to create a travel diary using a smartphone application, rMove, developed by RSG, over a period of 21 days. The data from the AMP project includes a smartphone travel diary and a post-diary survey. The smartphone travel diary provides information about all the trips made by each participant across all modes, and the post-diary survey measures overall perceived well-being outcomes across all the trips they made during the study period.

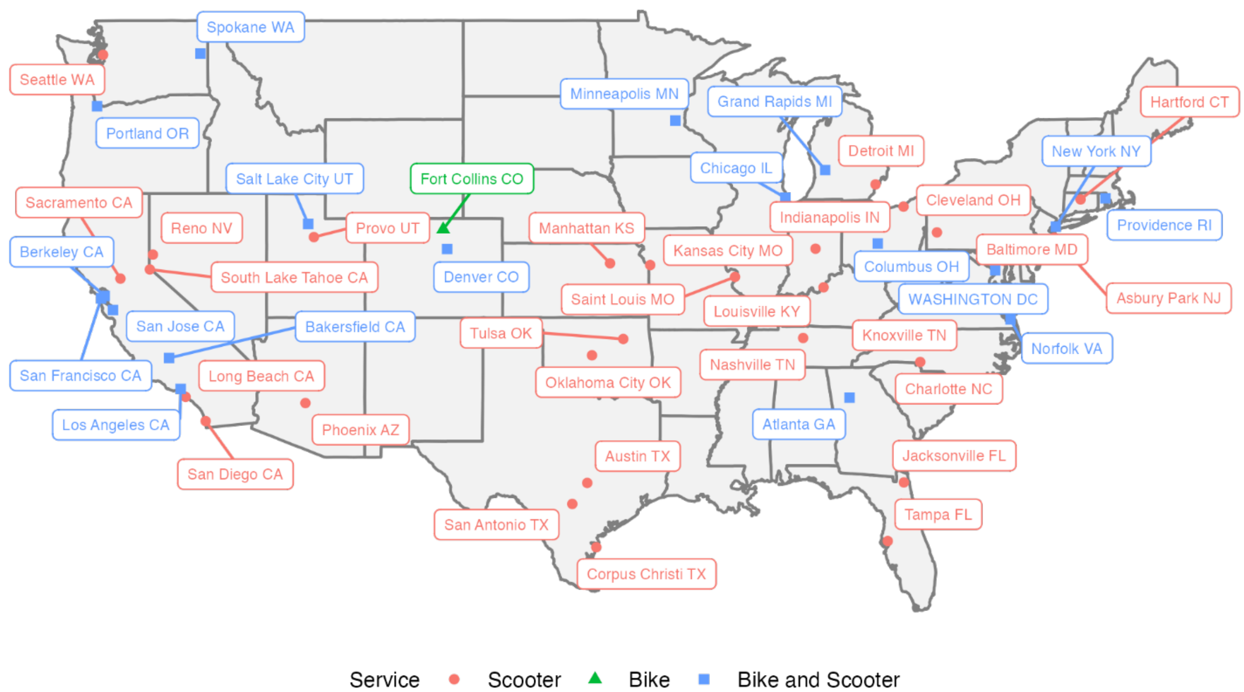

Figure 2.1
A map of the contiguous United States with the cities in the AMP project.

2.2 Data Collection

The data from the AMP project contains results from 2,206 participants who made 183,483 trips, before the data was cleaned. Because the post-diary survey was optional, only a subset of participants completed this survey, with one response for each participant. A summary of the participants who took the post-diary survey is in Table 2.1.

Table 2.1
Table of participant characteristics who took the post-diary survey.

Characteristic	Summary (n = 674)
Participants	674
Cities	42
Female	38.6%
White	72.4%
Income	
Less than $50k	23.4%
$50k to 100k	26.3%
$100k to 150k	18.8%
More than $150k	25.8%
Age	
Under 35	54.7%
35 to 55	36.2%
Over 55	8.01%

* Total percentage may not be 100% due to rounding.

As participants went about their days, rMove would use the GPS location of the participant's smartphone to determine whether the participant was relatively stationary at a location, such as at home or at work, or if they were making a trip from one location to a different location. If rMove decided that a participant was not traveling, rMove would internally establish geofenced areas around the participant. This area allows for the participant to have some movement at their location, such as walking around the convenience store while shopping, without causing rMove to mistakenly classify all movement as individual trips. When a participant moves outside of the geofenced area, rMove would decide the participant is making a trip and would begin recording their location as GPS traces at some intervals during the trip until it determined that they had stopped moving and therefore had reached their destination. After each trip, rMove prompted the participant to answer questions about the trip, such as the mode(s) used and the purpose of the trip.

In the smartphone app rMove, a series of short survey questions were presented to participants before they started the study and after the app detected completed travel (the "prompted recall travel diary"). The before-study questions included one-time measures of variables that do not change or were unlikely to change during the diary period, such as their sociodemographic characteristics. The travel diary questions included the labels for observed travel behavior, such as the mode used for the trip and the purpose of the trip.

Following the travel diary period, participants were invited to complete a post-travel diary survey online which included questions about their travel during the survey period. In the post-diary survey, participants were asked various questions of how their use of bike-share and scooter-share affected their perceived well-being. I use Likert-scale questions from the post-diary survey to better understand how a person's shared micromobility use affects their perceived well-being in this research.

The one-time online post-diary survey measured general travel behavior and perceptions of micromobility, and some effects of micromobility services on those outcomes. This post-diary survey was fielded in September 2022. Questions in the post travel diary survey included experiences with micromobility services, use of different transportation modes before the COVID-19 pandemic or at present, the effect of micromobility use on other transportation use, collision or almost collision experiences on or with micromobility vehicles, responses to questions about micromobility services and other aspects of transportation, and additional individual characteristics the travel diary survey did not include, such as types of living place and residential ownership.

2.3 Data Processing

The processing of the AMP data for modeling required two efforts: 1. processing of the shared micromobility trips and aggregating them at the person-level and 2. collecting data on the participants' characteristics, their post-diary survey responses, and their aggregated trip environment data to create the model variables.

The record for each trip taken by all the participants in the study contains information about the trip and identifies who made the trip. Most important for this analysis, each trip record comprises GPS traces recorded at some varied interval by the rMove smartphone application in the form of latitude and longitude coordinates. I filtered all the trips in the data to extract just trips made by shared micromobility modes; the three shared micromobility modes in the AMP study were bike share (conventional bike), bike share (e-bike), and scooter share. For the purposes of this analysis, I grouped conventional and e-bikes into a single bike share category. I also excluded outlier trips made by shared micromobility modes outside of the 48 cities in the AMP study. These trips were rare, and sometimes made outside of the United States, as participants continued to use rMove while traveling outside of their recruited city.

After filtering the data for the shared micromobility trips, I subset them by city and performed map matching (see below) to generate a trip path along the network. Map matching occurs at the trip level, but the infrastructure used by each person needed to be estimated at the person-level because the responses to the post-diary survey questions are at the person level rather than for each individual trip made. The transportation network used in the analysis was the OpenStreetMap (OSM) network (OpenStreetMap contributors, n.d.), which represents the real-world built transportation environment as a graph of nodes and edges. Each edge contains attributes about the segment of the trip, such as the maximum allowed speed or the number of lanes or the roadway class. To get trip-level data, I calculated weighted averages and standard deviations of these quantities, weighted by each segment distance within the matched trip. I calculated simple averages and standard deviations of each person's infrastructure exposure across their shared micromobility trips based on the number of trips they made for the model data. Once these variables were computed at the person-level, I was able to join them with the respondents' survey responses, demographics, and the city they were recruited in.

I hypothesize that some aspects of weather, like wind, humidity, or precipitation, could vary within a city throughout each day and influence one's perceptions of their trips or their willingness to make trips by micromobility. Therefore, I included weather exposure in my analysis. Weather variables for the model were treated in the same way as network-related variables and aggregated at the person level, thereby representing the average weather conditions across all the individual's trips. Open-source, historical weather data for each trip was collected from Open-Meteo (Open-Meteo, n.d.) for free programmatically.

2.4 Map Matching

2.4.1 Conceptual Model of Map Matching

To incorporate trip characteristics and infrastructure exposure into the model, the GPS traces of the trips must be matched to the network so that each trip can be associated with some level of infrastructure exposure. The individual GPS traces of each trip get compared with the graph representation of the city's street network so that each trip is translated into a path along the graph as a series of nodes and edges along the network.

I used the Leuven.MapMatching Python library (Meert and Verbeke, 2018) to map match the data. The algorithm is based on a Hidden Markov Model (HMM) with non-emitting states. The trip location data in the AMP project have GPS traces that are sometimes sparse. This presents a challenge in that each consecutive recorded trace in the trip's data may not be matched to adjacent nodes and links in the network graph. For example, a person may be traveling on a gridded street network, and a trace is recorded crossing First Street. However, there is a gap in time, and the next trace is crossing Third Street. Considering that First, Second, and Third Streets are all parallel, there are no direct connections between First and Third Streets and the person must have crossed Second Street. Therefore, the person must have traversed some edges and nodes that allowed them to cross Second Street.

The HMM with non-emitting states allows for the map matching model to accept that the user existed between the recorded traces, and that therefore there must be points that should be matched between these recorded states so that there is a contiguous matched trip between the trip start and trip end. This method allows for a contiguous and a likely complete representation of a participant's trip, although it does not necessarily guarantee the entire trip from start to end as the participant made it, nor the true path they took. The advantage of HMM over a simpler shortest-path algorithm is that HMM is generating possible edges to traverse in the graph (Newson and Krumm, 2009). Each possible edge is treated as a hidden state, with an assigned "emission" probability that defines the likelihood of the traveler being detected there with a GPS observation. The model assumes each observation is produced, or "emitted," by a hidden state. Between each position is a transition probability defining how likely it is for the traveler to move from their current position to the suggested hidden state. Additionally, with this method consecutive paths can be considered rather than treating each state transition as a discreet decision to be made. The Viterbi algorithm utilizes dynamic programming to consider these entire paths, and it works to maximize the probabilities of the emissions and the transitions to find the best route.

With technological limitations in collecting GPS traces, such as the tracking by the rMove smartphone application being limited by the smartphone operating system or the smartphone signal being obscured by the surrounding physical environment (e.g., tree canopy, tall buildings, bridges, tunnels, etc.), I assume the HMM used by Leuven.MapMatching provides for a reasonable representation of each shared micromobility trip by the participants, as it is considered a preferable method to map matching over other algorithms that rely on distance, like a shortest-path algorithm (Meister et al., 2021).

2.4.2 Preparing the Network for Map Matching

For the network data in my analysis, I used OSM to generate my network exposure variables. OSM is a crowdsourced map of the world that is free and open source (Haklay and Weber, 2008) that provides the street network infrastructure for every city in the AMP study. To acquire the OSM network for the areas around the GPS traces in the data to perform map matching, I utilized the Python library, OSMnx (Boeing, 2024). OSMnx allows users to request just the OSM network for areas of their choosing, so that downloading large OSM networks manually and loading them into Python can be avoided. For each city in the data, I generated a rectangular bounding box around the furthest extents of the GPS traces in all directions plus a small buffer to safeguard against trips along the boundaries of the rectangular network area being disconnected from the larger network and unable to be matched. This bounding box was given to OSMnx, which then extracted the OSM network for within the rectangular buffer for downloading.

OSMnx also allows for the requesting of network data based on the travel mode of analysis, such as requesting only the infrastructure where driving is allowed. For this analysis, I requested all infrastructure. I used OSMnx to also remove any directionality in the network, considering that bike-share and scooter-share users may travel on paths dedicated to only walking, or may travel in the opposite of the intended direction of some facilities. After retrieving the network, I removed facilities like expressways or access ramps that are exclusively used for vehicles so that the map matching algorithm would not incorrectly match trip paths to these edges and nodes.

The OSM network provided for most of the network exposure variables in my analysis. However, the network downloaded using OSMnx did not include any elevation data for the nodes, or grades for the edges. To generate the edge grades between nodes, I used the Python library Py3DEP (Chegini et al., 2021) to request digital elevation maps for my regions defined by my bounding boxes. Py3DEP provides these elevation maps from the U.S. Geological Survey (USGS) 3D Elevation Program (3DEP) (Thatcher et al., 2020). These elevation raster files were used by OSMnx to find the elevation for each node in the network, which were then used to calculate the absolute grades for each edge.

2.4.3 Linear Interpolation of GPS Traces

Before employing the map matching operation across all the shared micromobility trips in the data set, I explored a smaller subset of the trips in the city of Berkeley, California. Initial testing with just the HMM with non-emitting states on this subset of trips could not fully map match many of the trips from beginning to end. Even when considering the non-emitting states, trips may contain long trip segments that may not be overcome with the algorithm due to infrequent collecting of GPS traces by the rMove application. Because of this, additional preprocessing of the trips is sometimes useful to fully map match most of the trips.

For this analysis, I used linear interpolation to help reduce the sparsity of GPS traces in portions of the trip with longer segments. I calculated the segment distance between consecutive

GPS traces for each trip. If the segment distance exceeded my selected threshold of 0.1 miles $(d > \gamma)$, then linear interpolation was performed between the coordinates at the beginning (p_j) and the end of the segment (p_{j+1}) to produce m interpolated points based on the ratio of the segment distance and the predefined threshold.

$$m = \left\lfloor \frac{d}{\gamma} \right\rfloor - 1 \tag{2.1}$$

where

m	is the number of newly generated interpolated, equidistant points between GPS trace p_j and the subsequent trace p_{j+1}
d	is the segment distance in miles between GPS trace p_j and the subsequent trace p_{j+1}
$\gamma = 0.1\ miles$	is my defined threshold distance between GPS trace p_j and the subsequent trace p_{j+1} to determine if new traces should be generated between p_j and p_{j+1}

The linear interpolation distributes new, interpolated points at equal intervals between every GPS trace p_j and the subsequent trace p_{j+1}. I decided on a threshold of 0.1 miles so that there would be a frequent enough sequence of GPS traces to allow the map matching algorithm to proceed for most of each trip. See Figure 2.3 for an example of the linear interpolation process.

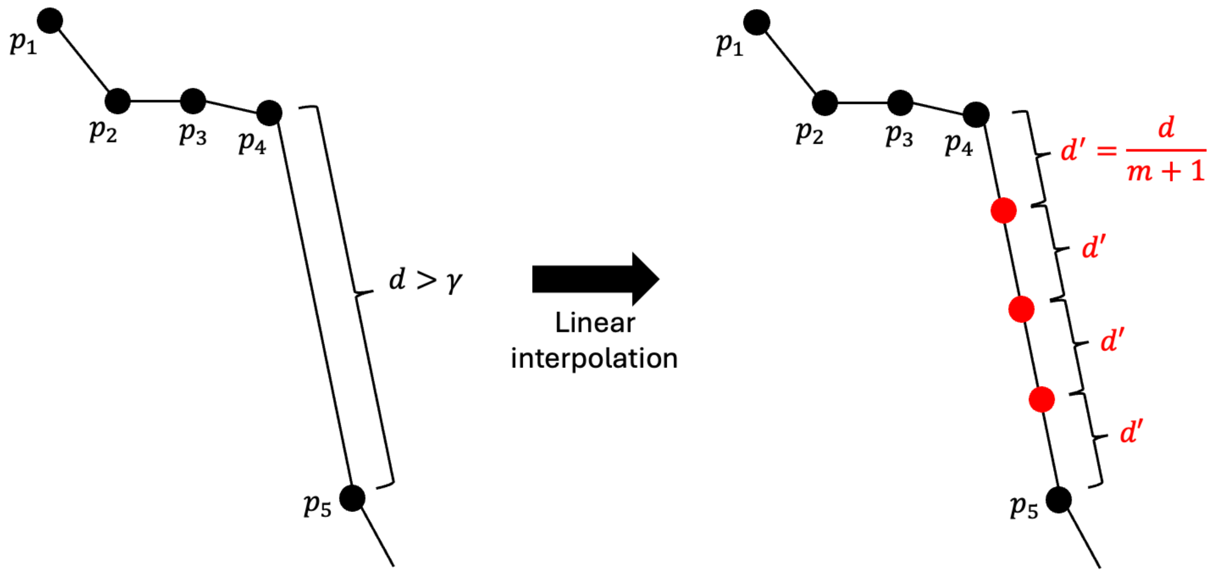

Figure 2.3
A demonstration of linear interpolation generating equidistant points between two points p_4 and p_5 with a distance between them that exceeds the threshold.

2.4.4 Map Matching Process

I filtered the AMP project trips made for just bike share and scooter share trips for this analysis. Each trip has a defined *market*, which describes the name of the city in which they were recruited. This was very useful because it is impractical to load the roadway network of the entire country at once and considering that the trips made in the AMP project occurred within dozens of cities across the country, manually downloading and subsetting the roadway network was impractical. Additionally, while shared micromobility trips are made within their respective operator's service boundaries, these service areas are not published as readily available and up to date shapefiles for researchers. This would also not consider users who stray outside of the service boundary for some distance. Downloading the network by city name was considered but not chosen due to the varying structures of municipalities across the country. Not all study areas may correspond to a single city and some municipal boundaries are defined by irregular shapes (Los Angeles). Some cities are the same as their respective county (San Francisco) while others may have counties within their cities (New York City). Retrieving the appropriate shapefiles from government sources while considering all these various legal definitions of each city proved to be unreasonable.

Instead, having each trip labeled by a *market* name allowed them to be grouped geographically very simply without processing any of the GPS traces first. Using the *market* label, the traces for every trip in the *market* were programmatically searched to find the furthest extents of every trace in all cardinal directions. These extents, plus a small buffer, were used to define a bounding box around the trips in every market. Any trip that occurred in a *market* is contained entirely within the *market's* bounding box.

Bounding boxes provided for a simple and straightforward way to define what street networks were relevant to the analysis and should be collected. OSMnx was able to read in these bounding boxes and retrieve the OSM network for each *market*. Py3DEP was able to do the same for the elevation rasters. The elevation rasters were paired with the OSM network, and the elevations for each node and grades for each edge on the graph were calculated by OSMnx. Next, I filtered out expressway facilities that are not accessible to shared micromobility. Each *market* now had a network to perform map matching with. I performed the linear interpolation to generate the necessary intermediary traces and then performed the map matching with Leuven.MapMatching so that every trip in the data had a path on the graph as a series of nodes and edges, which contained information about each node and edge to describe the real-world infrastructure.

2.5 Statistical Modeling

The health outcomes I modeled for this analysis are a series of discreet, ordered responses on a five-point Likert scale (e.g., *Strongly disagree*, *Somewhat disagree*, *Neither agree* *nor disagree*, *Somewhat agree*, or *Strongly agree*). I analyzed the unique contributions of the explanatory variables to the dependent variables through a multilevel cumulative (ordinal) logistic regression model, with a unique model for each health outcome: mental wellness, safety, and physical activity. Because the responses are on the Likert scale, the change in probability between *Strongly disagree* and *Somewhat disagree* is different than the change from *Strongly disagree* and *Neither agree nor disagree*, which suggests a greater change in perception than a step change in disagreement. This warranted a model with an ordered response variable. Additionally, I selected Bayesian estimation so that the model would allow for the interpretation of the probability of each category. This way, the results can be interpreted as the probability that a respondent would *Somewhat disagree* that riding bike-share is unsafe, for example.

Each model is at the person-level, nested in the city the participant was recruited from. Each model was built in R using the library brms (Bürkner, 2017). The general form of the models is as follows:

$$\log\left(\frac{Pr(y_i < k)}{1 - Pr(y_i < k)}\right) = \alpha_k + \alpha_{person[p]} + \alpha_{city[c]} - \sum_{m=1}^{M} \beta_m X_{m_i} \tag{2.2}$$

with the following priors:

$$\begin{aligned} (\alpha_1, \dots, \alpha_k) &\sim Normal(0, 1.5) \\ \alpha_{person} &\sim Normal(0, \sigma_{person}) \\ \alpha_{city} &\sim Normal(0, \sigma_{city}) \\ (\beta_1, \dots, \beta_m) &\sim Normal(0, 2.5) \\ (\sigma_{person}, \sigma_{city}) &\sim HalfNormal(1, 1) \end{aligned}$$

where

y_i is the response value

k	is a possible response category
$\log\left(\dfrac{Pr(y_i \leq k)}{1 - Pr(y_i \leq k)}\right)$	is the log-cumulative-odds that response value y_i is equal to or less than a possible response category $k_{(1,\ldots,5)}$
α_k	is the k thresholds between the $k+1$ ordinal response categories
$\alpha_{person[p]}$	is the vector of intercepts that vary by person, indexed by person p
$\alpha_{city[c]}$	is the vector of intercepts that vary by city, indexed by city c
X_{m_i}	is the predictor variable m
β_m	are the slopes for X_{m_i}
σ_{person}	is the standard deviation parameter for the person-level varying effect
σ_{city}	is the standard deviation parameter for the city-level varying effect

I selected priors based on prior work by Fitch et al. (2022) on ordinal models of bicycling comfort data on a seven-point scale, although slightly adjusted to be more restrictive and informative for the varying effect standard deviations because of limited number of measures for each person.

2.6 Model Selection

I used Leave One Out Cross Validation (LOO CV) using Pareto smoothed importance sampling (PSIS) to select a model that best represented the effects of the predictors on the response variable (Vehtari et al. 2017, Vehtari et al. 2024). LOO CV iterates with each observation in the model data set, removing it from the data and predicting that observation based on the remaining data and the model. PSIS estimates once with all observations and generates importance ratios. The largest are fit to a Pareto distribution to smooth their weights closer to their expected weights. If noisier values with a Pareto value exceed 0.7, these points are refitted to avoid the misleading approximation by PSIS. Afterwards, I compared the results of the LOO CV for each model by evaluating the difference between the theoretical expected log predictive density (ELPPM Difference) from each model with the most performant model as well as the standard error difference (SE Difference). The ELPPM describes an estimate of how well the model performs on new data.

2.7 Limitations

My methods and analyses have several limitations and assumptions which may or may not be able to be addressed by future research. First, the AMP project had a short survey period during the Summer 2022 with only one post-diary survey. The short time frame in which the trips occurred required me to make assumptions when generalizing about users' shared micromobility use across the travel diary period. The survey took place during the summer, and responses or travel behaviors may differ during other seasons. The post-diary survey was also distributed to participants in the study later in summer after the initial trip diary portion of the study had been completed. It is possible that the delay between when the trips occurred and when participants took the post-diary survey could mean that their responses are not fully accurate to how they felt about their trips at the time they made them. Each response they present about an aspect of the impact of shared micromobility, such as its effect on their mental health, is meant to reflect all their trips as a whole and may obscure the effect of the environment on their perceptions from individual trips. Because the survey captures longer-term perceptions rather than at the trip-level, the analysis focuses on these broader evaluations. However, this approach may not fully correspond to objectively measured changes in actual behavior or psychological outcomes. Relying on perceived rather than objective measures, which were not captured by the survey, presents an important limitation. Additionally, the recruitment process for the study was biased towards more frequent users of micromobility. This means that the trip attributes in the data may not represent a typical user's micromobility trips. Non-users of shared micromobility are not represented in the data, because only users of micromobility answered the survey questions for the analysis. Because the data represents only users of micromobility, the analysis may be missing perceptions of shared micromobility that could differ for non-users that would influence them not riding. If so, negative perceptions of shared micromobility are possibly underrepresented.

Another potential limitation is in the city coded data. The city attributed to each participant in the data is the city where they were recruited. However, this may not be where they made all or even most of their trips, which complicates using the city name as a factor to represent the influence of the built environment on their behavior and survey responses. Given that this analysis is on the person-level due to each person only having one response for the entirety of their trips in the post-diary survey means that I assume their recruit city best represents their overall exposure, especially for measures unexplained by network characteristics and weather based on their trip locations.

Additionally, because of the way the transportation network is built as a graph, infrastructure exposure is defined in this analysis by the infrastructure comprising of the links and nodes of the map matched trip. Consider a micromobility trip along a divided arterial in a dense urban area. The GPS traces will naturally have some jitter to them and deviate from the straight path of the arterial due to inaccuracies in the recording of the location of the smartphone device as well as possible interference by the built environment around the user (e.g., tall buildings, trees, overpasses, etc.). Also, the user may stay along this arterial for a significant distance, but they may make turns along this arterial. For example, for the first half mile the user may travel along the sidewalk on one side of the road, and then transition to a separated bike path, and then later travel along a bike lane adjacent to the vehicle lanes. In the network representation of this arterial, each of these three facilities may be represented by distinct, parallel sets of links and nodes. Therefore, exposure being defined by the matched path leads to a limitation of reduced information about the experience of the participant, as travel along the sidewalk will not contain information about neighboring facilities, such as the adjacent vehicle lanes. However, considering the broad scope of the project (covering a variety of cities across the continental United States), manual review to incorporate these adjacent features was not feasible. Additionally, assumptions regarding what infrastructure within a specified distance from a participant should be considered as exposure is challenging to define for a diverse set of urban environments which likely have region-specific characteristics. I performed this analysis under the assumption that such infrastructure exposure beyond the traveled path would be captured by the city-level variable, especially if shared micromobility operating areas are not physically large within cities and likely cover similar infrastructure within each operating area.

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3 Modeling Users' Perceived Effects of Shared Micromobility on Mental Wellness

3.1 Introduction

To date, the mental wellness implications of shared micromobility use remain underexplored. How we travel, and the built environment we travel within, influences not just our physical wellness but our mental wellness as well. There is growing interest among researchers and practitioners in articulating the relationship between transportation modalities and individual psychological well-being. Transportation is also undergoing rapid changes with the growth in popularity of shared micromobility systems, which have quickly expanded across cities in the United States and around the world. Research into how these shared micromobility systems have affected how people travel has become increasingly important to characterize the effects these new mobility options are having on our travel behavior and well-being.

Researchers have sought to link travel behavior and mode choice with the health outcomes of traveling by these modes and within the built environment. Active travel modes, like bicycling, walking, or riding micromobility, are generally associated with improved mental wellness as opposed to sedentary travel modes like driving a personal vehicle. However, less is known about how riding shared micromobility modes like bike share (both conventional bicycles and e-bikes) and scooter share (e-scooters) impact mental wellness. While shared micromobility use is usually considered an active mode of travel, many shared micromobility services comprise of electric-assist or fully electric bikes and scooters, which could impact a user differently than riding a personal bicycle or walking.

In this chapter I evaluated the mental wellness outcomes of shared micromobility use. I aimed to improve our understanding of how riding shared micromobility influences one's perceived mental wellness. To accomplish this, I used the survey and travel diary data collected from micromobility users across various cities in the United States during Summer 2022 as part of the American Micromobility Panel (AMP) project (Fitch et al., 2023). The post-diary survey included within the AMP project asked participants how their use of bike share and scooter share affected their stress levels, how relaxed they were when riding, and if it improved their overall mental health. I hypothesize that increased exposure leads to more positive responses from respondents about the effect of their shared micromobility use on their mental health despite the potential negative effects on mental health due to the perceived risks of using shared micromobility.

3.2 Literature Review

3.2.1 Transportation and Mental Wellness

Transportation is linked to both positive and negative impacts to one's health in general. A proposed conceptual model built on a review of recent studies of the health impacts of transportation (Glazener et al., 2021) posits that transportation can benefit a user by providing mobility, access to more amenities, and increased independence. For some modes, transportation can also lead to increased physical activity and exposure to green spaces. Increasing physical activity by replacing sedentary trips with trips by active modes of travel has both positive physical and mental health benefits (Abduljabbar et al., 2021). However, many negative impacts of transportation on health have been observed, such as damage to the environment, noise pollution, injuries and deaths from vehicles, and changes to land use and community planning around the automobile.

Mental wellness encompasses psychological experiences such as stress and relaxation. Stress is a result of factors of a person's physical and social environments (Pearlin, 1989). Lazarus (1984) presented a clear definition of stress: “Psychological stress is a particular relationship between the person and the environment that is appraised by the person as taxing or exceeding his or her resources and endangering his or her well-being (p. 19)." If a person feels they are in danger during an activity, they may react with increased stress. Milakis et al. (2020) note that although using micromobility may have positive effects on a person's subjective well-being, they may be counteracted by concerns of the perceived dangers of riding micromobility. Transportation has also been linked with detrimental effects to one's mental health in the form of increased stress. Those with longer commutes in a personal vehicle are more stressed and less satisfied (Han et al., 2022). While commuting in general tends to reduce one's mood, active travel modes are better for one's mood although outcomes like mood are dependent on a person's unique characteristics (Lancée et al., 2017). While driving increases stress, other active modes of travel have been proven to reduce stress. Yang et al. (2021) studied measured stress responses from respondents as they used various modes of travel, and found that bicycling and walking reduced stress, while driving increased stress. As general bicycling reduces stress (Avila-Palencia et al., 2017), it is expected the same can occur for users of bike share. For example, survey respondents reported "reduced stress" since joining the bike share (Alberts et al., 2012). The research reviewed by Abduljabbar et al. (2021) found these mental health benefits for non-electric shared micromobility. Researchers have also begun to investigate scooter share to see if riding scooter share provides similar effects on one's mental health as traditional active travel modes, like bicycling and walking. Results of surveying e-scooter users in the United Kingdom showed that most users had positive mental health effects of using e-scooters, and reduced stress during and after their trips (Grant-Muller et al., 2023). While respondents did report reduced stress during e-scooter trips, other research has shown that interactions with motor vehicles increases the stress of a bicyclist (Gadsby et al., 2021). Milakis et al. (2020) note that although using micromobility may have positive effects on a person's subjective well-being, they may be counteracted by concerns of the perceived dangers of riding micromobility. This may or may not be a result of the mode, bicycle vs. e-scooter, and it could also relate to the environment of the studies.

Satisfaction or pleasure may be key in counteracting other negative effects, like increased stress due to safety concerns. Wild and Woodward (2019) showed that bicyclists have a higher sense of satisfaction with their commutes likely because of the increased physical activity and potential for social interaction. While riding micromobility in locations without protected infrastructure may induce stress for the user when they feel in danger, the physical activity required for traveling and the possibility for taking routes away from traffic congestion may also provide stress relief for traveling. It is especially interesting to study how these potential benefits to a user's mental health are affected by how they use shared micromobility, such as for commuting or leisure, as well as if this benefit is reported by users who also still drive a personal vehicle for some trips. These mental health advantages may or may not outweigh the potential disadvantages depending on the travel purpose for the micromobility trips by the user, the micromobility mode, and the characteristics of the user. The link between mental health and shared micromobility use is less explored due to the relatively recent emergence in shared micromobility services.

3.2.2 Travel Environment and Mental Wellness

Literature has shown that the built environment a person travels through, including the types of streets they use or the steepness of those streets, influences aspects of their mental wellness. Bolouki (2023) reviewed neurobiology literature and found that the natural environment is more calming than the urban environment, and that reducing stimulation of the senses is key to relaxation. One way to reduce stimulation could be to travel on quieter and less busy streets instead of high traffic corridors. For example, Fitch et al. (2020) found that streets like local roads with lower speeds and lower traffic volumes are less stressful for bicyclists than larger, high-volume streets. On these local streets, bicycles also can exert their priority in traffic because vehicles are traveling slower. However, this study was limited in scope and number of participants, as equipping the student participants with the biometric sensors required preparation and limited the possible cycling routes and total distance. Reducing the stress experienced by cyclists with a tool for city-wide bike facility planning has been explored with marginal rate of substitution values for slope, number of lanes, and bike facilities (Lowry et al., 2016) derived from research by Hood et al. (2011) and Broach et al. (2012). With mood surveys, Glasgow et al. (2019) found that natural travel environments had a positive effect on travelers' moods. While Glasgow et al. (2019) acknowledged that they observed differences in travel mood across participant demographics, such as race, ethnicity, and gender, they did not explore any of these differences and suggest that further results are needed before any conclusions on these results can be made. On the other hand, Willis et al. (2013) did not find a relationship between bicyclist satisfaction and the characteristics of the built environment. Their research was limited by not knowing the routes cyclists took to campus from home, and by only having a sample population of students at that specific university, where there will be less variety in built environment characteristics. These studies emphasize the relevance of built environment characteristics along the routes taken by shared micromobility trips when studying the effects of micromobility use on the mental well-being of the user.

3.2.3 Research Motivation

The current transportation literature has begun to explore how travel mode affects mental wellness through various pathways. Morris and Guerra (2015) studied the impact of travel on mood using data from the American Time Use Survey. They found that travel is not unenjoyable compared to activities like working and that travel does not strongly affect mood. However, they did find that bicycling had a more positive effect on mood compared to other modes of travel. Glasgow et al. (2019) also found that active travel improved moods compared to vehicle modes, but they did not include scooter share. Their findings do suggest that the natural and urban environment features should be expanded upon. These findings of improved mood align with Wild and Woodward's (2019) determination that bicyclists are more satisfied with their commutes. Bicyclists have a higher sense of satisfaction with their commutes likely because of the increased physical activity and potential for social interaction (Wild and Woodward, 2019). Additionally, the effects of bicycling may differ for shared micromobility use (Wild and Woodward, 2019). Handy and Thigpen (2019) found that the satisfaction with one's commute is a result of the quality of the travel, and that active travel results in higher satisfaction. Also, Grant-Muller et al. (2023) identified reduced stress because of e-scooter use.

These results suggest there are multiple opportunities for a commute mode to affect one's mental wellness. However, mood, satisfaction, and stress are separate and specific measures that may influence a person's broader sense of mental wellness, though they do not describe mental wellness more generally. This is important as De Vos et al. (2019) have proposed that satisfaction with travel and the travel mode could influence additional travel by that mode, which would be an important effect to consider for planners and practitioners aiming to increase active travel. If perceived mental wellness in general improves with shared micromobility use similar to individual measures documented in the literature, perhaps there is an effect of encouraging more shared micromobility use. I endeavored to model a more general impact on perceived mental wellness as a result of a person's shared micromobility use that included multiple measurements of perceived mental wellness. I am interested in whether shared micromobility specifically carries the same positive impact as other, traditional active travel modes like bicycling and walking described above.

3.2.4 Definition of Mental Wellness

In this dissertation, I examine perceived mental wellness through three dimensions: perceived changes in mental health, perceived changes in stress, and perceived changes in feeling relaxed. Although some overlap among these dimensions is possible, each was included in the AMP project survey to represent a different facet of perceived mental wellness. "Mental health" is understood as a form of mental well-being irrespective of any mental illness (World Health Organization, 2004) which considers positive or negative feelings and a person's psychological functioning (Keyes, 2002). Mental health is the broadest out of the three dimensions and is expected in this study to encapsulate how a respondent felt about the changes in their overall mental state more generally. For example, if travel is a significant part of one's daily routine, any improvements in the quality of travel would be expected to reflect in perceived improvements to their mental health. "Stress" is expected to function just as defined by Pearlin (1989) and Lazarus (1984) and reflect the risks and danger one feels while traveling. In the psychology literature, "relaxed" is a positive-affect emotion associated with calmness and being at ease, with lower arousal and positive valence (Russell, 1980). The inclusion of "feeling relaxed" in the survey was meant to capture a general sense of calmness and comfort while riding micromobility. The expectation is that one could feel some instances of stress while riding due to risky characteristics of their travel environment (e.g., navigating a busy intersection with unprotected bike lanes along their regular commute path) but also feel relaxed in general using a micromobility device (e.g., the act of riding a bike share e-bike is calming to a person independent of the quality of the facilities they bike on). Taken together, mental health, stress, and relaxation are meant to define a person's mental wellness in this study.

3.3 Methods

3.3.1 Study Design

This study leverages the AMP project travel diary and survey data to link responses about mental wellness after using shared micromobility with characteristics of the participants and the trips they made on bike share and scooter share. Considering that stress is a critical component of a person's mental health, and stress responses can originate from a person's physical environment, I incorporate characteristics of the built environment based on the trips each respondent made using shared micromobility in my analysis. The AMP travel diary provides the trips respondents made using shared micromobility. The AMP post-diary survey includes the demographics of the participants, which can be linked to their trips.

I also considered the impact of participant age, gender, and income on the perceived effects on mental health. Additionally, having information on all their shared micromobility trips allows me to determine each user's exposure to shared micromobility, in time used per survey days. I leverage the data on the routes of each trip taken by each user that is included in the AMP data. Like Glasgow et al. (2019), the AMP project reduces recall bias by having participants journal their responses in the smartphone app to the travel diary questions once a trip has been completed.

In this paper, I model how a user's shared micromobility use and exposure to the environment from their trips affects their perceived mental wellness. This research investigates if increased exposure to shared micromobility use improves a user's perceived mental health, reduces stress after a trip, or if users are relaxed while riding shared micromobility. This research avoids limitations faced by prior studies with little or no information about the actual routes taken by participants in considering the relationship between the built environment and a bike share and scooter share riders' responses about their use of shared micromobility. Existing research on the mental wellness impacts of shared micromobility, especially electric devices, is limited; therefore, this analysis of the AMP data will provide a unique and valuable contribution to the existing body of literature.

3.3.2 Model Description

To evaluate the perceived mental wellness outcomes from using shared micromobility, the results from six post diary survey questions covering dimensions of mental wellness are modeled as a function of participants' characteristics, their use of shared micromobility, and their exposure to weather and the built environment. Three dimensions of perceived mental wellness, *mental health*, *stress reduce*, and *relaxed*, are measured for both bike share and scooter share with ordinal responses to the survey questions shown in Table 3.1. Because the true mental wellness state of a user cannot be directly observed, perceived mental wellness serves as a proxy. The ordinal survey questions have responses on the five-point Likert scale, where *Strongly disagree* is the most negative response towards the effects of shared micromobility and *Strongly agree* is the most positive response towards the perceived effects of shared micromobility across all three dimensions of mental wellness. For analysis, I converted the data to a format where each response to the six Likert-scale questions appears on a separate row, within a single response variable. Each response contributed one observation to the model, and a respondent identifier was retained to preserve within-person dependence across items. Given that the resulting responses are ordinal, I modeled the outcome using a generalized ordinal logistic regression.

Table 3.1
Description of the response variable for the mental wellness model.

Mental Wellness Dimension	Survey Question
Mental Health	Riding a bike-share bike improves my mental health Riding a scooter-share scooter improves my mental health
Stress Reduce	After riding a bike-share bike, I feel less stressed than I did before my trip After riding a scooter-share scooter, I feel less stressed than I did before my trip
Relaxed	I feel relaxed while riding a bike-share bike I feel relaxed while riding a scooter-share scooter

Responses are on the following Likert scale:
Strongly disagree, *Somewhat disagree*, *Neither agree nor disagree*, *Somewhat agree*, *Strongly agree*

The predictor variables were selected to capture information about the participant that may affect their perceptions in the response variable. These include variables such as the participant's *city* (the city in which they were recruited for the AMP study), which is the primary way to represent the unobserved characteristics of a participant's environment of their micromobility use in the model, aggregated travel environment measurements (such as weather during micromobility trips and street characteristics), and sociodemographic characteristics. Figure 3.1 shows the conceptual model with all the predictors included in each model.

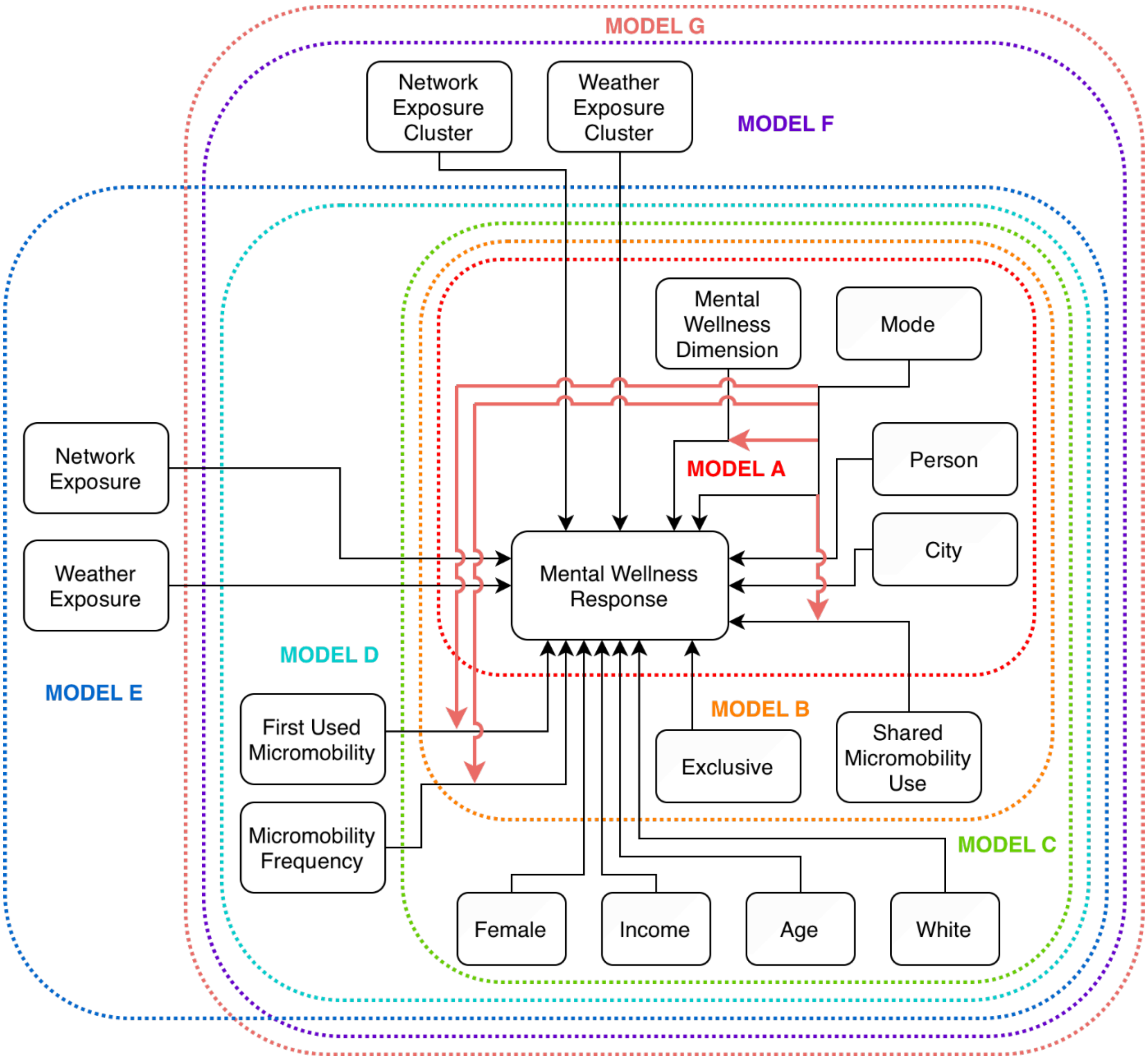

Figure 3.1
Diagram of the mental wellness conceptual model.

Observations in the data are identified by *mode* – if they are about bike share or scooter share – and if the participant is an *exclusive* user of either bike share or scooter share or a non-exclusive user of shared micromobility modes. Bike share use and scooter share use can differ, such as by trip purpose or trip length, and they require different levels of skills to operate, such as knowing how to ride a bicycle. Users are expected to be more comfortable with shared micromobility use if they use both modes, as opposed to those who exclusively use one mode and who may be less familiar to these systems. Additionally, the participant's *shared micromobility use* is included (i.e., general use of the shared micromobility mode in total trip duration per survey days), which is the primary predictor of interest. Each participant has a unique shared micromobility use value in units of minutes per day to represent their total exposure for each shared micromobility mode that they used.

3.3.3 Data Summaries

The results of the post-diary survey questions used to create the mental wellness response variable are displayed in Figures 3.2-3.4. Users are more likely to agree than disagree that riding shared micromobility improves their mental health (Figure 3.2). More than half of scooter share users agree, and most users of bike share riders agree. Very few disagree that bike share improves their mental health, and slightly more users disagree for scooter share, which aligns with users agreeing less. Scooter share users were also far more neutral about it improving their mental health compared to using bike share.

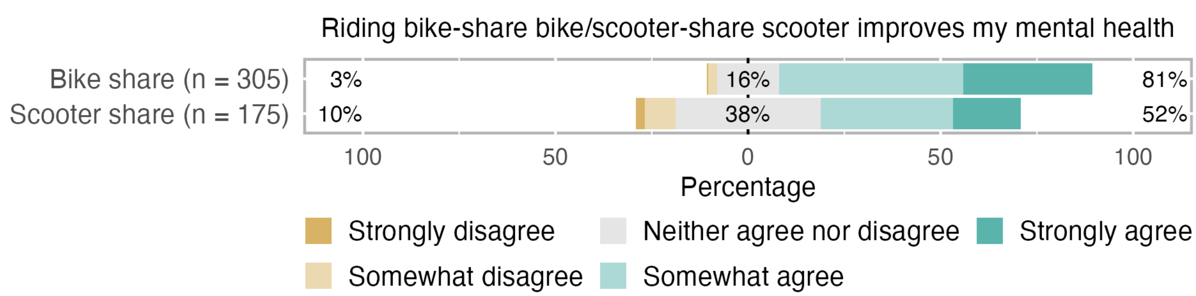

Figure 3.2
Users' perception of riding shared micromobility improving their mental health by mode.

Respondents mostly agree they feel less stressed after riding bike share and scooter share than they did before their trip (Figure 3.3). Again, users agree less and disagree slightly more with scooter share than with bike share, while also remaining significantly more neutral. Notably, no majority agreed that scooter share reduced their stress levels after riding, unlike the previous finding where a majority agreed that scooter share improved their mental health.

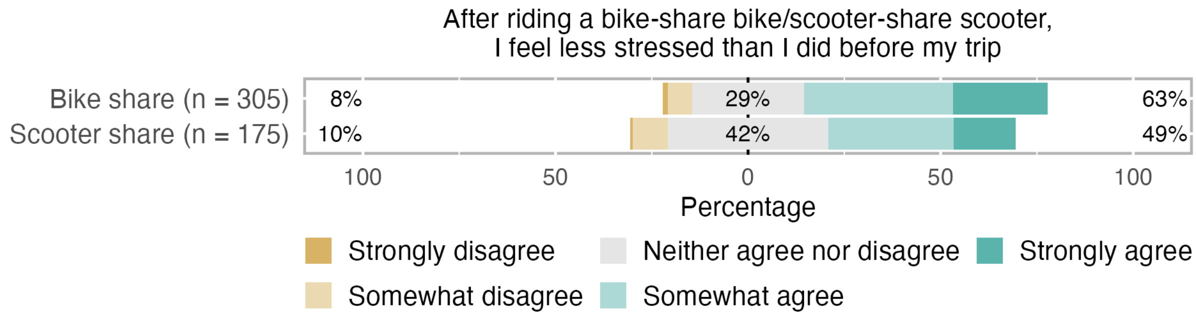

Figure 3.3
Users' perception of feeling less stressed after riding shared micromobility by mode.

Again, users are mostly in agreement that they feel relaxed while riding both bike share and scooter share services (Figure 3.4). However, feeling relaxed while riding elicited the highest share of disagreement out of the three questions, for scooter share at 14%, and the least amount of neutral responses for scooter share by a significant amount. It appears, out of the three questions, feeling relaxed while riding is the aspect of mental wellness that had the most disagreement, especially with riding scooter share.

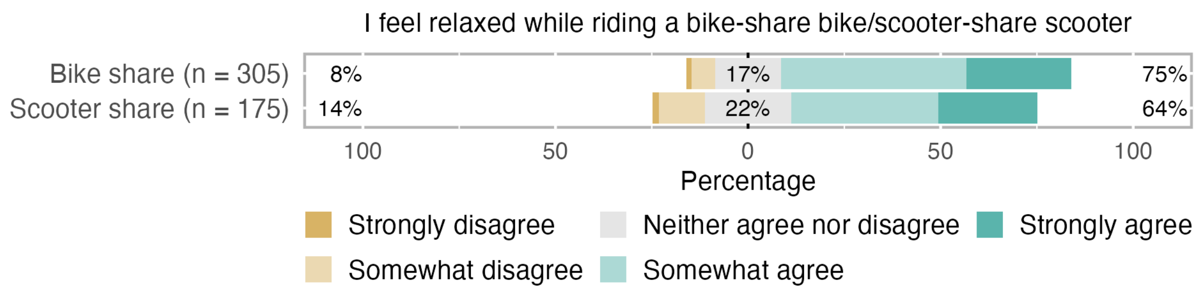

Figure 3.4
Users' perception of feeling relaxed while riding shared micromobility by mode.

The stronger and more positive responses regarding the impacts of riding bike share on one's perceived mental wellness is more pronounced when considering that riding bike share accounts for most of the observations in the model data. While there are many more scooter share services in the AMP project (Figure 2.1), there is more participation in the post-diary survey by users who only use or also use bike share. This may be a result of AMP prioritizing the recruitment of frequent shared micromobility users, and the bike share services being older and more established than scooter share services.

Table 3.2 shows the summary of the participants' sociodemographic characteristics in the data for the models. There are 427 unique participants in the data for the models, and each of these variables in the table have a single unique value per person, except for *Shared Micromobility Use*, in which case a person may have a value for both bike share and scooter share, or maybe just one value for the one mode they exclusively used. Additionally, variables that make up a participant's exposure to the network, or the weather they experienced, are aggregated to their exposure averaged over all the trips they have taken by shared micromobility.

Table 3.2
Summary of the participant characteristics used in the analysis.

Characteristic	Percentage (n = 427)
Exclusive Users	85.7
Female	34.0
White	74.5
Age Under 35	52.9
Age 35 to 55	38.4
Age Over 55	8.7
Income Less than $50k	23.9
Income $50k to 100k	28.3
Income $100k to 150k	19.4
Income More than $150k	28.3

I expect that when users ride micromobility longer on average per day, their responses regarding the effects of shared micromobility on their mental wellness will improve. To complement the average daily use of shared micromobility, I have also included their familiarity with both services based on when they first used them in the model. This helps capture their exposure to shared micromobility and comfort with riding these bikes and scooters. As expected, bike share is more represented than scooter share and is skewed towards first using it more than one year ago (Table 3.3). This makes sense considering that scooter share is a newer service compared to bike share, despite scooter share being more ubiquitous in our study cities.

Table 3.3
Percentage of when each participant first used bike share and scooter share.

First Used	Bike share (n = 305)	Scooter share (n = 175)
Less than 6 months ago	7.2	15.4
6 months to a year ago	6.9	10.3
1 to 2 years ago	15.7	22.9
More than 2 years ago	70.2	51.4

Bike share use is more distributed amongst higher frequencies of use compared to scooter share, with just under half (45.9%) of bike share users responding that their perceived use of bike share is for *5+ trips a week*. Scooter share users were much more evenly distributed amongst frequencies between *1-3 trips a month* to *5+ trips a week* (Table 3.4). This may suggest more comfort or familiarity with riding bike share compared to with riding scooter share. It could also suggest a difference in the utility bike share or scooter share provide, if frequent shared micromobility users regularly use bike share but selectively use scooter share.

Table 3.4
Percentage of how often each participant reported they used bike share and scooter share.

Frequency	Bike share (n = 305)	Scooter share (n = 175)
Never	0.0	1.7
Less than one trip a month	4.6	9.7
1-3 trips a month	9.8	21.1
1-2 trips a week	18.7	21.7
3-4 trips a week	21.0	16.6
5+ trips a week	45.9	29.1

In addition to experience, the model contains information about their experiences with the built environment and the weather during the shared micromobility trips they made. Summaries of participants' exposure to the environment, through three network predictors and three weather predictors, are shown in Table 3.5. Participants did not travel on very steep street segments on average, and street segments would typically have between two and three lanes. When participants made their trips, precipitation was low, but the trips were in humid weather with a range of low wind speeds.

Table 3.5
Summary of participants' exposure to the environment.

Variable	Mean	SD
Mean Weighted Absolute Average Grade	0.014	0.009
Mean Weighted Average Number of Lanes	2.558	0.599
Mean Proportion Residential	0.163	0.189
Mean Relative Humidity (2 m)	70.146	14.325
Mean Precipitation	0.110	0.297
Mean Windspeed (10 m)	12.743	6.010

The trips participants made with shared micromobility resulted in an average of just over 10 minutes on bike share per day, and just under six minutes on scooter share per day (Table 3.6). The large standard deviations suggest that there is a diverse range of daily shared micromobility use across the participants in the study.

Table 3.6
Summary of participants' use of bike share and scooter share in minutes per day.

Mode	Mean	SD
Bike share	10.69	11.71
Scooter share	5.95	8.98

To further characterize the experience of each participant as they used shared micromobility, the city in which they were recruited for the AMP project was included in the model. Out of the 48 unique cities in the AMP project, the participants in my model data were recruited from 32 of the cities. Not all cities in the AMP project are represented in the model data because some participants did not answer the post diary survey questions for the response variable. The percentage of the total 427 participants from each city is shown below in Table 3.7. As expected, most participants are from the denser, higher population cities. The four cities of Chicago, New York City, San Francisco, and Washington, D.C. have a combined 59.5% of the participants. Larger cities dominating the percentage of participants is to be expected considering how much smaller some of the other recruitment cities are. However, I expect the variety of large cities in the data, which cover many regions within the United States and unique topologies and climates, will allow the results to be relevant for interpretation beyond these cities.

Table 3.7
Summary of which cities participants were recruited in.

City	Percentage of Participants (n = 427)
Atlanta, GA	1.4
Austin, TX	1.4
Baltimore, MD	0.9
Berkeley, CA	2.1
Charlotte, NC	1.2
Chicago, IL	16.6
Columbus, OH	2.1
Denver, CO	6.1
Detroit, MI	0.2
Fort Collins, CO	0.2
Grand Rapids, MI	0.5
Indianapolis, IN	0.5
Long Beach, CA	2.1
Los Angeles, CA	4.0
Louisville, KY	0.5
Minneapolis, MN	4.2
Nashville, TN	0.2
Norfolk, VA	0.2
New York, NY	14.8
Pittsburgh, PA	0.2
Portland, OR	4.7
Providence, RI	1.4
Reno, NV	0.2
Sacramento, CA	1.4
Salt Lake City, UT	0.5
San Diego, CA	0.5
San Francisco, CA	12.2
San Jose, CA	1.6
Seattle, WA	0.9
Spokane, WA	0.5
Tampa, FL	0.7
Washington, D.C.	15.9

Three network variables from the various built environment exposures collected from the map matching process were selected for my modeling: *Mean Weighted Average Absolute Grade*, *Mean Proportion Residential*, and *Mean Weighted Average Number of Lanes* (Figure 3.5). These three were chosen as they encompass the main experiences of riding on a network (averaged across an individual's trips) that can be measured with the information provided by OpenStreetMap. There are many different classifications of streets as they are divided into discreet segments. For the experience of a shared micromobility rider, the literature suggests that it is most important to identify in the model how often participants were experiencing streets that have higher traffic capacity (Gadsby et al., 2021), and how often they choose lower volume traffic streets (Broach et al., 2012). Additionally, riding bike share requires some physical effort, so including the slope is appropriate (Broach et al., 2012). For example, a participant may be less likely to feel relaxed after riding bike share if they mostly ride on steep slopes than someone who rides on flat, quiet neighborhood streets. Most trips occurred on relatively flat terrain, with most of their trip occurring off residential streets and on two or three lane segments (Figure 3.5).

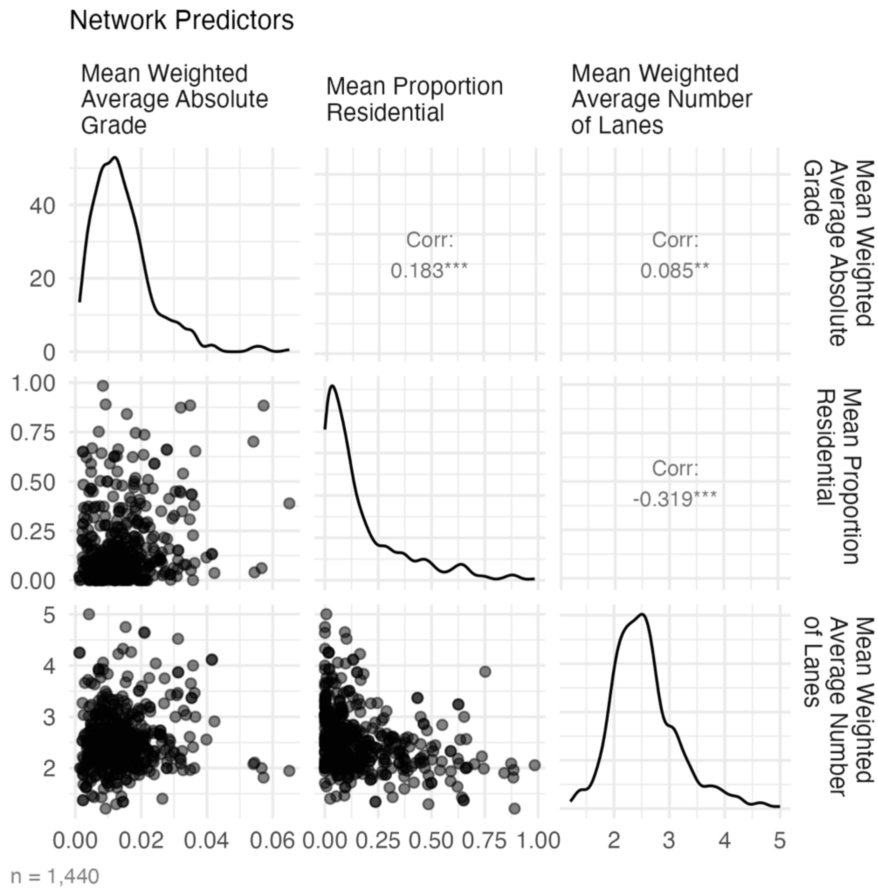

Figure 3.5
Distributions of the network variables in the models.

The three weather variables I selected for my modeling were *Mean Relative Humidity (2 m)*, *Mean Precipitation*, and *Mean Windspeed (10 m)* (Figure 3.6). These three weather characteristics are likely to vary over the trips a participant takes during the survey period, even within the same city. Therefore, the effect of weather may not be entirely captured by the city variable. However, shared micromobility service areas do not always cover large expanses of a city, so for some locations the weather experience on a day may be very similar across those users. Additionally, the AMP travel diary period was not a long enough time to include seasons other than summer, or a variety of changes in weather. Therefore, it appears that most participants did not experience rain while riding, but the humidity and wind speed did vary across participants' experiences (Figure 3.6).

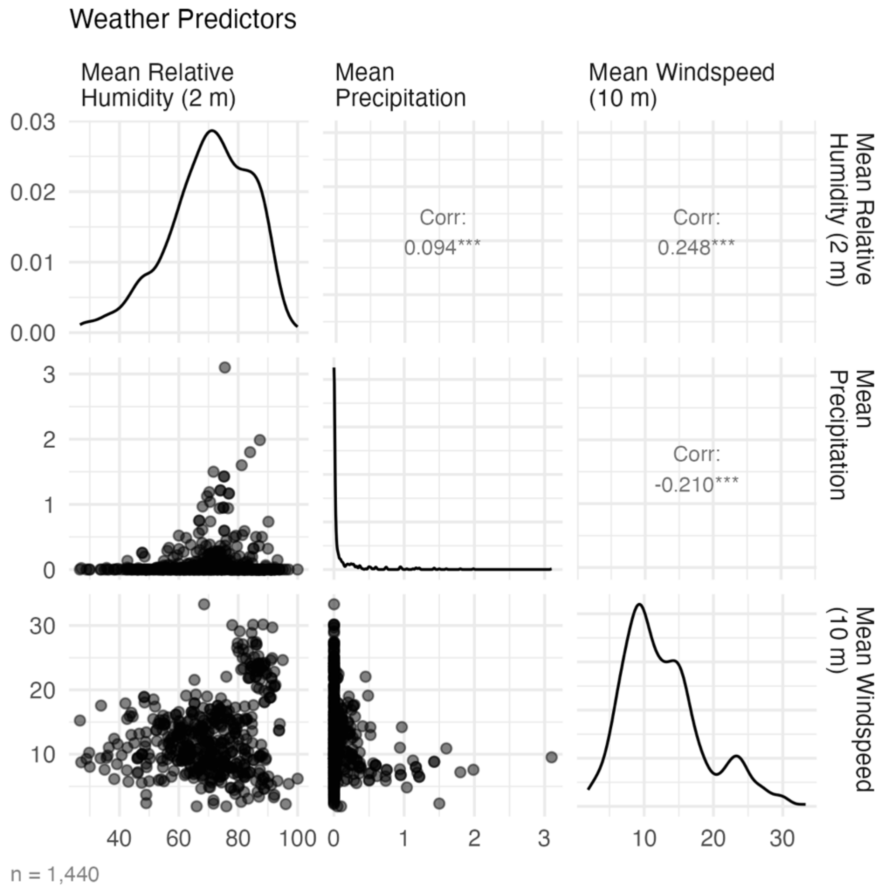

Figure 3.6
Distributions of the weather variables in the models.

I expected that across the network variables, and across the weather variables, each group of variables will have a directionally similar influence on the response variable. I clustered individuals based on their overall network and weather exposure profiles, once for the network variables and once for the weather variables. Individuals with similar values across the network variables were assigned to the same network exposure cluster and individuals with similar values across the weather variables were assigned to the same weather exposure cluster. Each cluster represents a distinct category of network or weather exposure that will make it easier to describe the effects of these exposures on the users' perceived mental wellness (e.g., exposure to windy and humid days compared to dry days with no wind).

I used the k-means clustering method to cluster the predictor variables to create the network exposure cluster and the weather exposure cluster. In each case, to determine the number of clusters, I employed two methods for evaluating the number of clusters and decided based on their performance: the Elbow Method and the Silhouette Analysis. The Elbow Method compares the total within-clusters sum of squares – the total of all squared distances between each cluster centroid and the observations within each cluster - across an increasing number of clusters, from 1 to a predetermined limit of the number of clusters. In this analysis, I selected 10 as my maximum number of clusters. As the number of clusters increases, the total within cluster sum of squares decreases as each observation is bound to be closer to a new cluster centroid. An ideal number of clusters is the point at which adding more clusters does not significantly reduce the total within-cluster sum of squares compared to the current number of clusters. In other words, this would mean identifying an "elbow" in the plot of number of clusters against the total within-cluster sum of squares. I also performed a Silhouette Analysis because there will not always be a clearly defined elbow. The Silhouette Analysis is a process by which, for each observation, a silhouette value is calculated to describe if the observation is well classified compared to neighboring clusters. A silhouette value considers the average distance between the observation and every other observation within its cluster as well as the average distance between the observation and observations in the neighboring cluster to describe if the classification is appropriate for that observation with the number of clusters that were used. Each observation has a silhouette width on a scale of -1 to 1, with larger values describing a better fit for that observation. The Silhouette Analysis computes the average silhouette width across all observations for each number of clusters. The ideal number of clusters for the observations would be where the Average Silhouette Width is the highest.

3.3.4 Clustering Based on the Network Variables

Using the Elbow Method, there is not an obvious "elbow" in the plot of total within-cluster SS per number of clusters that would indicate an ideal number of clusters (Figure 3.7). Based on this plot, it would be reasonable to consider 2, 3, or 4 clusters, as the reduction in the total within cluster sum of squares is less pronounced for 5 or more clusters. Any larger number of clusters begins to seem unreasonable for the sample size of observations in the model data, and the limited range of values for the network variables. Based on the Silhouette Analysis, using 2 clusters produces the largest average silhouette width which drops sharply with clusters of 3 or more. Because the Elbow Method does not offer a clear number of clusters to select, I deferred to the Silhouette Analysis to make my decision of 2 clusters using k-means clustering on the network exposure predictors.

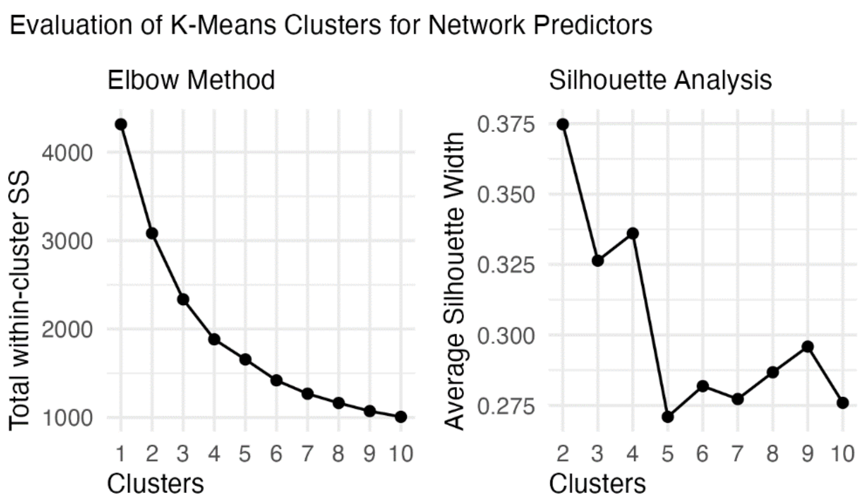

Figure 3.7
Evaluation of the number of k-means clusters for the clustering based on the network predictors.

The result of the k-means clustering for the network exposure predictors is shown in Figure 3.8. Plotting the data color-coded by the clusters, the clusters appear to be defined by the mean proportion of residential segments within the trips. Cluster 1 contains the participants who mostly did not travel on residential streets on average, while Cluster 2 is defined by having participants who had higher on average proportions of residential streets in their trips. Between Cluster 1 and Cluster 2, they do not differ much between the mean weighted average absolute grade, but participants who traveled on steeper slopes on average generally reside in Cluster 2. Similarly, both clusters have participants on average traveling on streets with a range of average number of lanes, but Cluster 1 generally has participants traveling on streets with more lanes on average. Overall, the new clustered network exposure predictor is defined by a cluster named *Less Residential* (Cluster 1) which contains participants with trips with less residential street segments, flatter, and streets with more lanes on average, and a cluster named *More Residential* (Cluster 2) that contains participants with trips with more residential street segments with steeper slopes and less lanes on average.

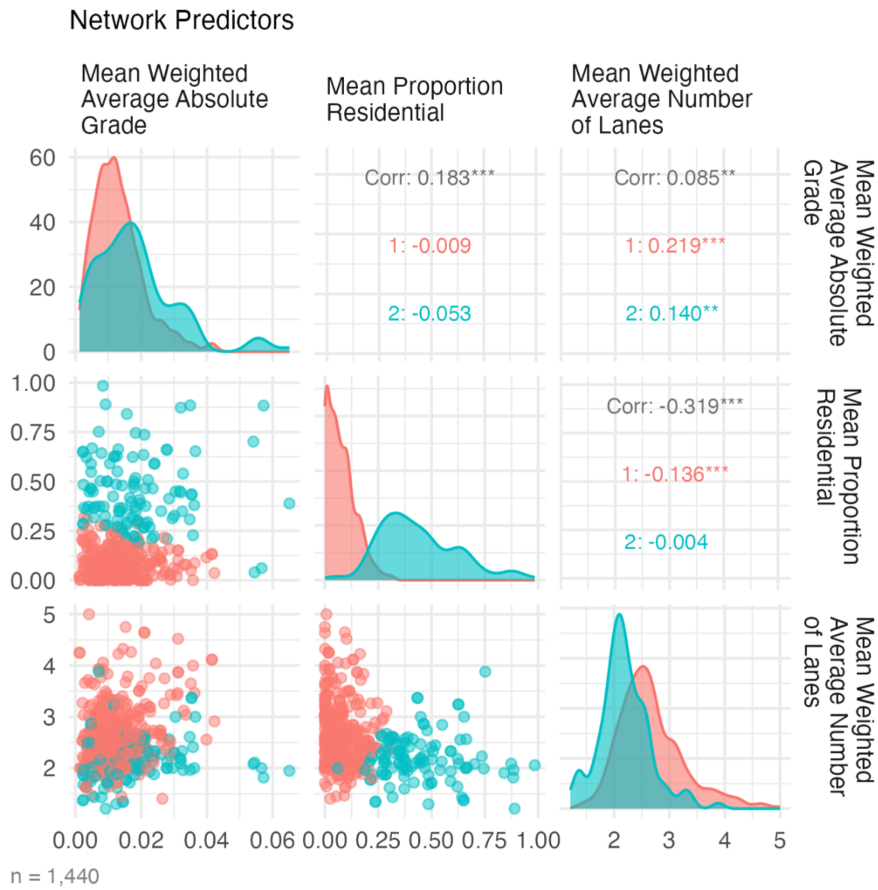

Figure 3.8
Results of clustering participants by the network exposure predictors.

3.3.5 Clustering Based on the Weather Variables

The clustering based on the weather variables followed the same method as I described for the network variables. According to Figure 3.9, the Elbow Method suggests that 3 or 4 clusters would be ideal for the weather variables. Based on the Silhouette Analysis, 3 clusters are significantly better than 4 clusters. When deciding between 3 and 4 clusters for the weather data, I considered that the fewer number of clusters there are, especially for three variables and a limited number of observations in the model data, it would make interpretation of the clusters and their effects on the response variable simpler and more meaningful in the discussion.

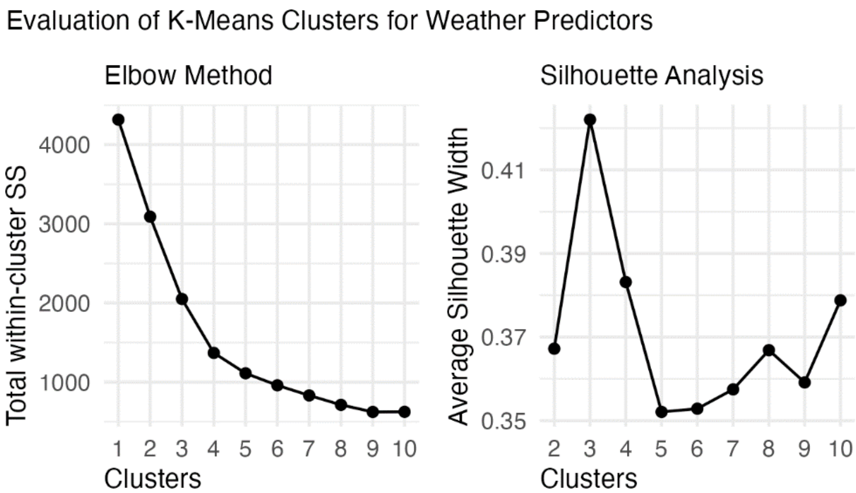

Figure 3.9
Evaluation of the number of k-means clusters for the clustering based on the weather predictors.

Figure 3.10 demonstrates the weather variable data color-coded by the three clusters determined by the k-means clustering algorithm. Cluster 1 appears to contain the participants who on average experienced rain and more humidity during their trips. Cluster 1 also tends to have participants who on average experienced less wind during their trips. Therefore, Cluster 1 is named *Humid and Wet Weather*. Cluster 2 is notably drier than Clusters 1 and 3, with the less humidity and less rain with moderate windspeeds and is named *Dry Weather*. Cluster 3 is named *Humid and Windy Weather* because it contains participants who on average experienced windier and mostly humid weather during their trips.

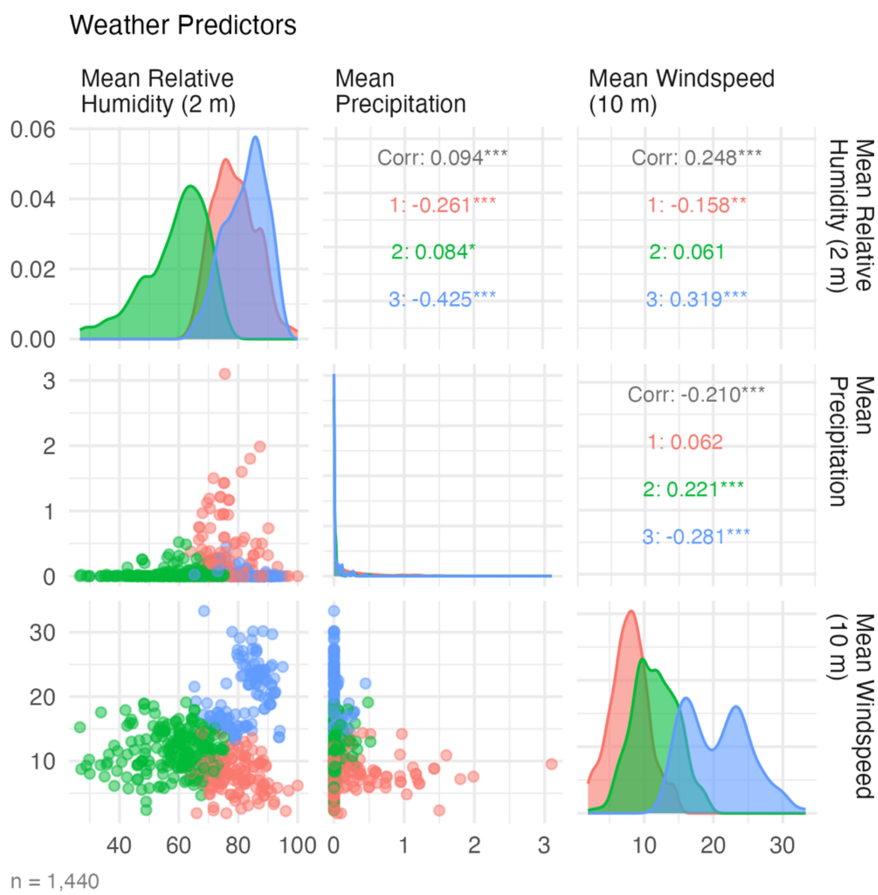

Figure 3.10
Results of clustering participants by the weather exposure predictors.

3.3.6 Model Descriptions

I created seven models to evaluate the impacts of the various predictors on perceived mental wellness based on the general model described mathematically in Chapter 2 Methodology. I began with a simple model, and each subsequent model increases in complexity by introducing a new set of predictors, which are organized thematically by their expected contribution to the model, as visualized in Figure 3.1. The goal of this approach was to identify which model would adequately explain the variation in the outcome while considering the trade-offs between model complexity and predictive performance. A summary of the seven models is shown in Table 3.8.

The simplest model, Model A, contains what I considered to be the essential predictors of the analysis: the *mental wellness dimension*, *person*, *city*, and *mode*. The *mental wellness dimension* identifies which of the three mental wellness dimensions the ordinal response refers to. *Person* and *city* identify the response at the person-level and city-level, respectively. *Mode* identifies if the response is about bike share or scooter share. Model B builds upon Model A by introducing objective measures of use of shared micromobility with a predictor to determine if the respondent exclusively uses that mode or not, and a predictor that is a measure of how much the respondent uses the shared micromobility mode in minutes per day. Importantly, the predictor for shared micromobility use is transformed by natural log due to the suspected non-linear effect on the outcome variable. This non-linear – diminishing returns – effect is assumed because conceptually using more shared micromobility is unlikely to cause a linear increase in measures such as mental wellness. Instead, I expect it to likely have diminishing returns with increased shared micromobility use. Model C builds upon Model B by adding sociodemographic predictors in addition to the baseline predictors and the objective measures of use of shared micromobility. These sociodemographic predictors include whether the respondent is female or not female, whether the respondent is within a certain income bracket, whether the respondent is within a certain age bracket, and whether the respondent is White or not White. Model D builds upon Model C by adding perceived shared micromobility experience based on how long ago a participant thinks they first used the service and perceived shared micromobility use based on how often a participant thinks they use the service. Model E introduces environmental exposure with the previously described network predictors (three predictors) and weather predictors (also three predictors). Model F includes all the predictors as Model D, but instead of introducing all the environmental exposure predictors, it includes two predictors based on the clustering: one for the network exposure cluster and another for the weather exposure cluster. Model G builds upon Model F by introducing interactions between the mode and mode-based predictors.

Table 3.8
Descriptions of each mental wellness model.

Model	Description
A	Mental Wellness Dimension + Person + City + Mode
B	Model A + objective measures of shared micromobility use
C	Model B + sociodemographic predictors
D	Model C + perceived shared micromobility experience and use
E	Model D + environmental exposure predictors
F	Model D + network exposure cluster + weather exposure cluster
G	Model F + interactions between mode and mode-dependent predictors

3.4 Results

The results comparing the models based on LOO CV are shown in Table 3.9 where each model is listed in order from highest performing to worst performing. According to the results of comparing the LOO CV of each model, Model G may perform best on new data, and it is the model I have selected for drawing inferences. That Model G performed best suggests that all the predictors I have selected for my analysis, from sociodemographic predictors to indicators of perceived use to network and weather exposure, are relevant for estimating users' perceived effects of shared micromobility on their mental wellness. Additionally, the comparison reinforces the value of predictors like environmental exposure and perceived experience and use of micromobility in modeling perceived impacts to mental wellness considering the next three performant models, Models D, E, and F, also include those predictors and the worst performant models, Models C, B, and A, do not.

Table 3.9
Results of comparing the LOO CV of each model.

Model	ELPPM Difference	SE Difference
G	0.0	0.0
D	-15.1	5.8
E	-15.4	6.0
F	-15.7	5.8
C	-30.5	7.4
B	-32.1	7.7
A	-43.2	8.7

The results below are based on Model G, which performed the best based on LOO CV. The results of Model G in Figure 3.11 describe the average rating of a shared micromobility user's response towards their mental wellness because of their use of shared micromobility. The predictor *shared micromobility use* in minutes per day was transformed by natural log due to the suspected non-linear effect on the outcome variable. This non-linear – diminishing returns – effect is assumed because conceptually using more shared micromobility is unlikely to cause a linear increase in measures such as mental wellness. I present the results for mental wellness as a latent variable scaled between 1 and 5, where the lower the values represent disagreement, and the higher values represent agreement with shared micromobility use having a positive effect on a user's mental wellness. I chose to present the results this way instead of as discrete values because a user's perceived mental wellness will occupy a spectrum between strong disagreement and strong agreement, and I am more interested in the range of negative or positive responses rather than the specific difference between categories of responses.

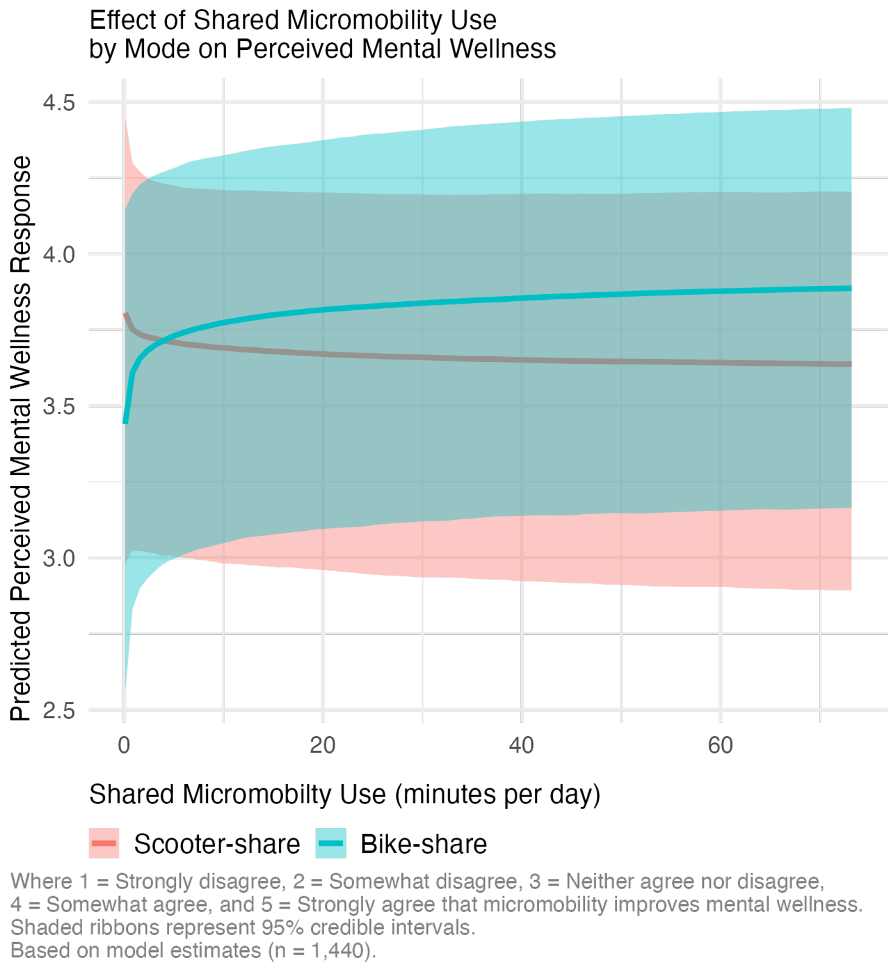

Figure 3.11
Conditional effects of shared micromobility use by mode on perceived mental wellness.

While the conditional effects of shared micromobility use by mode on predicted perceived mental wellness response (Figure 3.11) demonstrates a large amount of uncertainty, the mean within the interval still deserves discussion. Notably, there appears to be a difference between bike share and scooter share in how it impacts perceived mental wellness as a function of a user's use per day. Bike share use above 5 minutes per day is expected to result in a positive perceived mental wellness, above a response of 3.0 which is neutral. Additionally, the mean interval of bike share has a noticeable, sharply positive trend for that first 10 minutes per day of use. Based on this curve, a person that introduces at least 10 minutes per day of bike share use to their routine could, on average, see a 0.5-point swing in the positive direction for their predicted perceived mental wellness response. This increase in practical terms could likely change someone's response from *Neither Agree nor Disagree* that riding bike share improves their mental health to *Somewhat Agree*, for example. Scooter share on the other hand, demonstrates a different trend in the relationship between perceived mental wellness as a function of use per day. The results suggest that on average, a person who increases their daily scooter share use will see a slight decrease in their perceived mental wellness. Unlike bike share, scooter share shows a very flat trend as use per day increases.

Shared micromobility use describes daily use of the services and their impacts, but the model also includes when the user thinks they first used the service, which represents experience with the shared service. Figure 3.12 shows that, on average, a person who first used shared micromobility *more than 2 years ago* is more likely than a person who just started using shared micromobility recently to perceive that their shared micromobility use improves their mental wellness for both bike share and scooter share. This benefit is less pronounced for scooter share, and the perceived mental wellness does not change very much across time intervals within the past two years. For bike share, this benefit appears to increase throughout the first year of use.

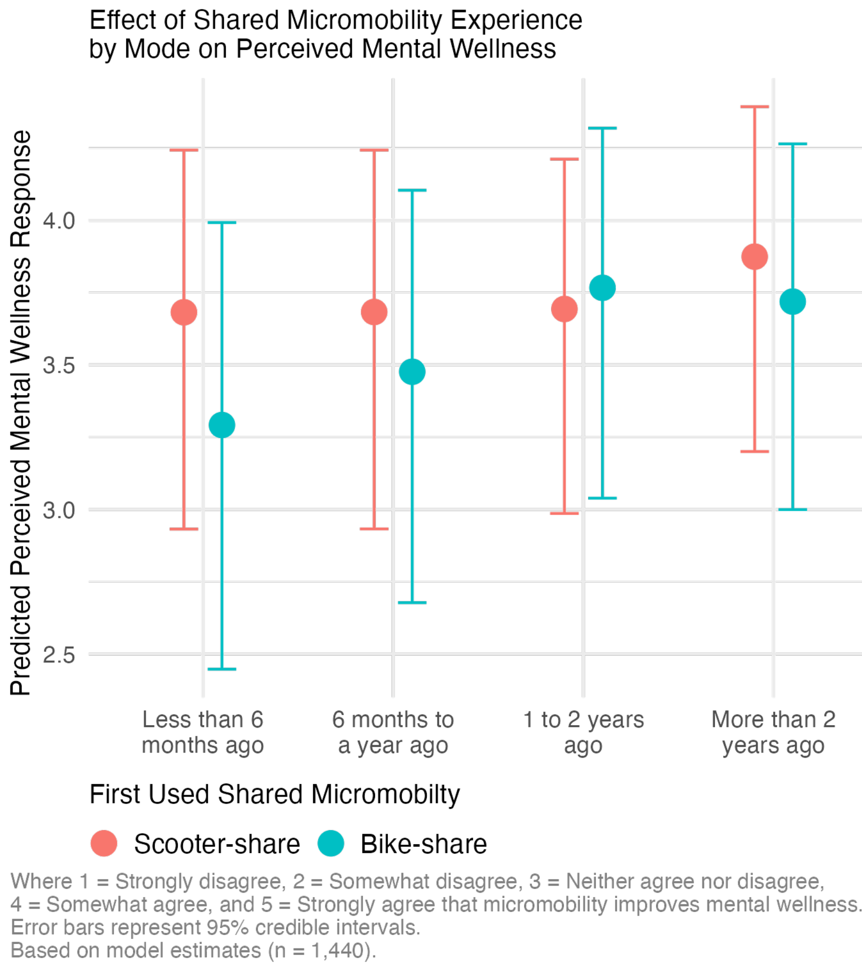

Figure 3.12
Conditional effects of shared micromobility experience by mode on perceived mental wellness.

While the effect of age is generally uncertain, on average the participants with ages *Over 55* are predicted to think that using shared micromobility improves their mental wellness more than those under 55 (Figure 3.13). On the other hand, there is predicted to be no difference between the predicted perceived mental wellness between the age groups of *Under 35* and *35 to 55*.

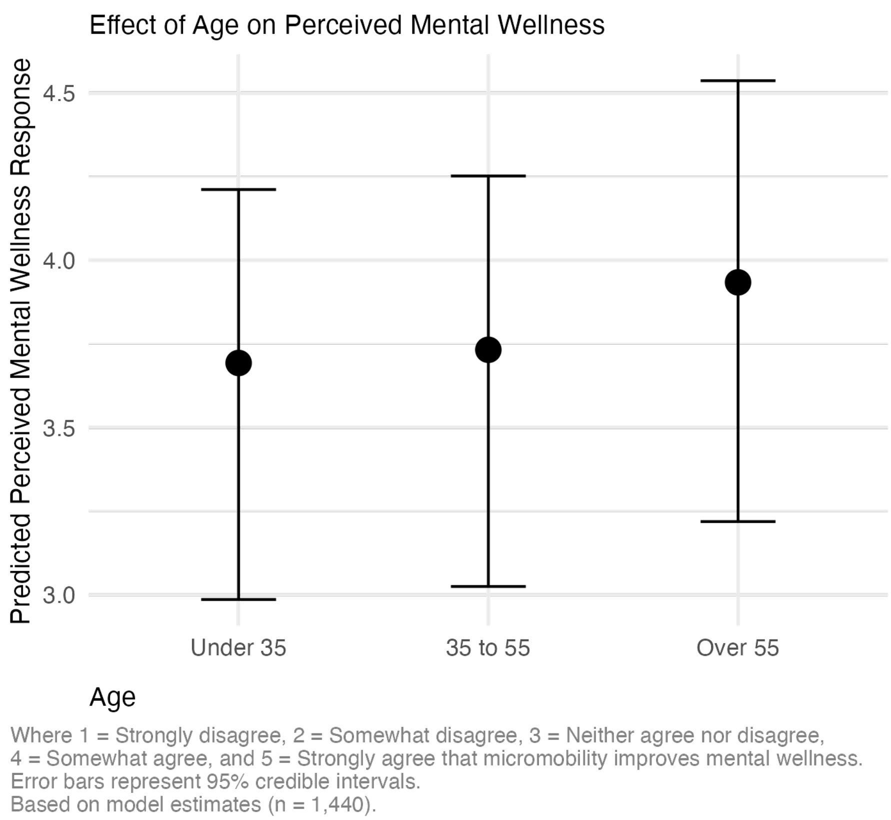

Figure 3.13
Conditional effects of age on perceived mental wellness.

Based on the posterior densities of the standard deviation parameters (Figure 3.14), we can be confident about *City* (city-level identifier) due to the distribution being so close to 0 and less than 1. The *Invitation Code* (person-level identifier) is much more certain and concentrated around just under three. According to this result, we can expect more of an effect from the person-level than from the city-level identifier and the mental wellness dimension, and a noticeable effect from the person-level.

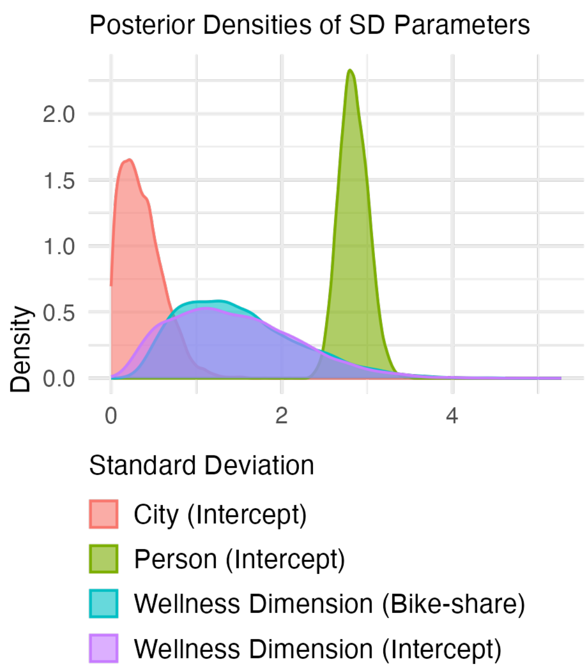

Figure 3.14
Posterior densities of the SD parameters.

According to the random effects of the mental wellness dimensions plotted in Figure 3.15, there is notable uncertainty. The error bars for both *Mental Health* and *Reduce Stress* extend both negative and positive, suggesting that it is possible the intercepts for these two dimensions are closer to the mean than *Relaxed*. *Relaxed*, while uncertain, will mostly have a more positive intercept compared to the mean.

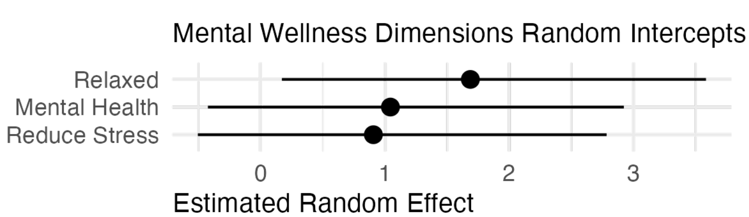

Figure 3.15
Estimated random effects by mental wellness dimension.

From Figure 3.16, city intercepts have much more uncertainty and they all generally straddle zero, implying they are not very much different than the overall mean. Portland, OR, Charlotte, NC, San Jose, CA, and Washington, D.C., show some difference from the rest of the cities. However, three of these four cities (Portland, Charlotte, and San Jose) have very few participants in relation to the total population, which may explain the slightly reduced uncertainty and the deviation compared to the other cities. Washington, D.C., on the other hand, is not an uncommon city in the data. Figure 3.16 shows that Washington, D.C., would likely have an effect of reducing one's perceived mental wellness as a result of riding shared micromobility, although again the effect is not strong or very certain. Therefore, while some cities show some slight change in the random effect compared to other cities, the city in which a participant is recruited from is not as meaningful. According to Figure 3.17, person level intercepts have a range of positive and negative effects, and narrower error bars in relation to their random effects. This may suggest that the person level variation is more meaningful to the model than the city level. *City* is unlikely to explain the differences in perceived shared micromobility unlike *person*, which shows more potential change in perceived mental wellness between individuals.

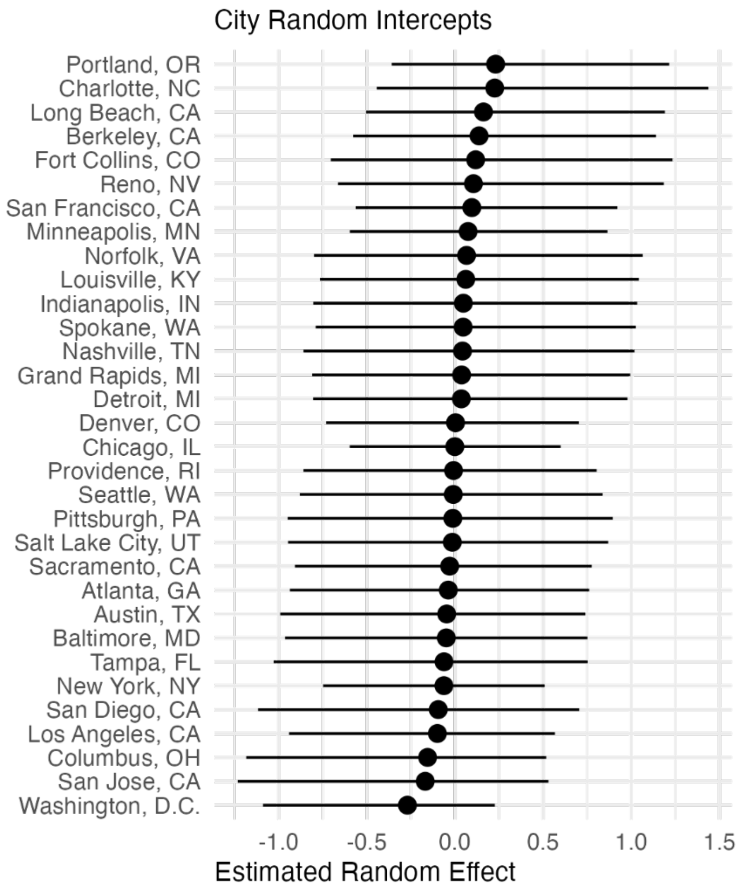

Figure 3.16
Estimated random effects by city.

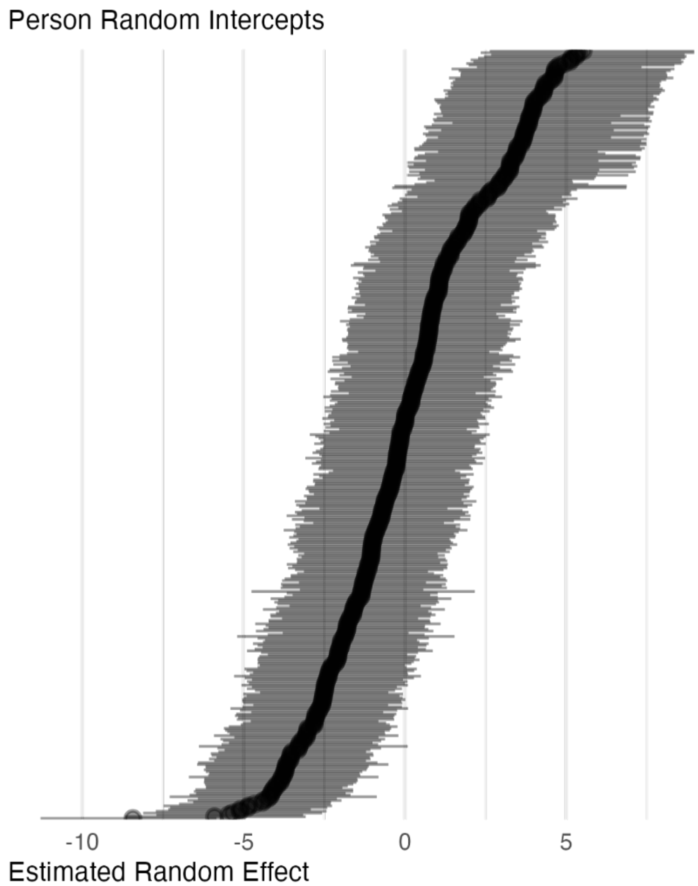

Figure 3.17
Estimated random effects by person.

Table 3.10 summarizes the model results. We can see that it is more probable that a participant would agree than disagree that the use of shared micromobility has a positive impact on their mental wellness. Additionally, many predictor effects are uncertain, and no specific predictors among network exposure, weather exposure, sociodemographic characteristics, or frequency stand out as having noteworthy impacts on the perceived mental wellness. *More Residential* does not show higher odds of an increase in agreement for mental wellness compared to *Less Residential* considering that the 95% confidence interval is uncertain in both the positive and negative direction. *Dry Weather* and *Humid and Windy Weather* also do not show strong effects in either the positive or negative direction compared to *Humid and Wet Weather*. However

Dry Weather is expected to have a slightly more positive effect on perceived mental wellness and *Humid and Windy Weather* a slightly more negative effect compared to *Humid and Wet Weather*. Instead, the main takeaways from the results are the differences between bike share and scooter share.

Table 3.10
Summary statistics of the selected final Mental Wellness model, Model G.

Parameter	Estimate	Est. Error	l-95% CI	u-95% CI
Intercept[1]	-6.6	1.2	-8.9	-4.2
Intercept[2]	-4.0	1.2	-6.2	-1.6
Intercept[3]	-0.9	1.2	-3.1	1.4
Intercept[4]	2.9	1.2	0.7	5.3
Bike share	-0.4	1.3	-3.2	2.0
Exclusive	-0.5	0.5	-1.6	0.5
log(Shared Micromobility Use (minutes per day))	-0.1	0.2	-0.4	0.3
Female	-0.4	0.3	-1.1	0.3
Income $50k to $100k	-0.6	0.4	-1.4	0.3
Income $100k to $150k	0.3	0.5	-0.7	1.3
Income More than $150k	-0.9	0.5	-1.9	0.0
Age 35 to 55	0.1	0.3	-0.5	0.8
Age Over 55	0.9	0.6	-0.2	2.1
White	0.2	0.4	-0.5	0.9
First used 6 months to a year ago	0.0	0.7	-1.5	1.4
First used Less than 6 months ago	0.0	0.7	-1.4	1.3
First used More than 2 years ago	0.7	0.5	-0.3	1.6
Frequency Never	-0.9	1.4	-3.8	1.8
Frequency Less than one trip a month	-3.3	0.7	-4.7	-1.9
Frequency 1 to 3 trips a month	-1.3	0.6	-2.6	-0.1
Frequency 1 to 2 trips a week	-1.8	0.6	-2.9	-0.6
Frequency 3 to 4 trips a week	-0.5	0.6	-1.6	0.6
Dry Weather	0.2	0.4	-0.6	1.0
Humid and Windy Weather	-0.1	0.5	-1.0	0.8
More Residential	0.2	0.4	-0.6	0.9
Bike share:Exclusive	0.0	0.5	-0.9	1.0
Bike share:log(Shared Micromobility Use (minutes per day))	0.3	0.2	-0.1	0.8
Bike share:First used 6 months to a year ago	-0.9	0.9	-2.7	0.8
Bike share:First used Less than 6 months ago	-1.5	0.9	-3.3	0.1
Bike share:First used More than 2 years ago	-0.9	0.6	-2.0	0.2
Bike share:Frequency Less than one trip a month	1.3	0.9	-0.5	3.1
Bike share:Frequency 1 to 3 trips a month	0.8	0.9	-0.9	2.5
Bike share:Frequency 1 to 2 trips a week	1.7	0.7	0.2	3.2
Bike share:Frequency 3 to 4 trips a week	0.8	0.7	-0.5	2.1

3.5 Conclusions

Based on the conditional effects of shared micromobility use in minutes per day by mode (Figure 3.11), introducing daily bike share use to one's daily routine may have a noticeable, positive impact on a person's perceived mental wellness for that first 10 minutes per day of use. In other words, introducing a single round trip or two on shared micromobility daily on average to a person who typically does not use shared micromobility will have the most benefit in improving their perceived mental wellness. However, if a person is just interested in using shared micromobility for its potential mental wellness benefits, my results suggest they should prefer bike share over scooter share for short, daily use. Scooter share is less likely to impact a person's perceived mental wellness as a function of their daily use, and on average the first few minutes per day of scooter share use may slightly reduce one's perceived mental wellness. The hypothesized non-linear effect of shared micromobility use outcomes is revealed in the diminishing returns in improved perceived mental wellness as shared micromobility use increases. This difference between the experience of riding bike share and scooter share suggests that riders would perceive an effect on their mental health, feeling of stress, or feeling relaxed. The difference between bike share and scooter share could be explained by some unobserved measures in the model, such as how the vehicle handles while riding or how other vehicles treat bike share or scooter share. Additionally, the findings suggest that not only is it recommended to introduce bike share to improve one's perception of their mental wellness, it is also beneficial to remain a user of bike share over time as the model predicts that the longer a person has experience with bike share, the more positive their perceived mental wellness will be (Figure 3.12). Regardless of gender, it is possible that as people age, they will be more likely to feel that riding shared micromobility has improved their mental wellness overall, although this effect is not strong and is uncertain, and mostly observed for ages *over 55* years old (Figure 3.13). This impact is also more dependent on an individual, and less on the city where the individual chooses to make their trips.

3.6 Discussion

With this chapter, I investigated the impacts of shared micromobility on one's perceived mental wellness. I wanted to determine if riding shared micromobility could be an avenue for people to improve their mental wellness through an activity that they must otherwise complete, if by a different mode. Travel is largely unavoidable, so if a mode of travel shows potential for benefits to one's wellness, even their perceived wellness, it warrants further research. The results from this chapter suggest that there is potential for bike share use being beneficial from a mental-wellness standpoint, although the model results demonstrate notable uncertainty. Despite this, respondents generally responded favorably that shared micromobility use improved their mental wellness, and therefore the idea is worth further exploration. The results show that future work should make an effort to include more characteristics about the individual, and that built environment or weather exposure is less important. On the other hand, the level at which the built environment and weather were included in the model – aggregated across all micromobility trips to the person-level – may have obscured the effect of these experiences on the perceived mental wellness, which was reported once after the travel diary period was completed. Future work should attempt to mitigate this disconnect between the travel experience and reported perceived mental wellness impacts, which may reveal relationships not apparent in my results. More survey questions on the topic of mental wellness would have been helpful in teasing out the differences between each participant's perceived changes in mental wellness, especially if these survey questions could be administered over time to observe changes as their shared micromobility use changes. It is also plausible that the direction of causality introduced in this analysis – shared micromobility use influencing perceived mental wellness – could also exist in reverse with perceived mental wellness impacting how shared micromobility is used. Therefore, it is possible that those riders who already perceive mental wellness benefits from riding would be more likely to increase riding. This potential for reverse causality has been noted by De Vos et al. (2019) between travel satisfaction and choosing active travel modes, and the same could be true for shared micromobility use.

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3.8 Appendix

Table 3.11
Mental Wellness Model A summary statistics.

Parameter	Estimate	Est. Error	l-95% CI	u-95% CI
Intercept[1]	-4.7	0.8	-6.1	-3.0
Intercept[2]	-2.2	0.8	-3.6	-0.6
Intercept[3]	0.7	0.8	-0.7	2.3
Intercept[4]	4.2	0.8	2.7	5.8
Bike share	1.2	0.2	0.8	1.5

Table 3.12
Mental Wellness Model B summary statistics.

Parameter	Estimate	Est. Error	l-95% CI	u-95% CI
Intercept[1]	-4.5	0.9	-6.2	-2.8
Intercept[2]	-2.0	0.9	-3.6	-0.3
Intercept[3]	0.9	0.9	-0.7	2.6
Intercept[4]	4.4	0.9	2.8	6.2
Bike share	1.0	0.2	0.6	1.4
Exclusive	-0.3	0.4	-1.1	0.5
log(Shared Micromobility Use (minutes per day))	0.3	0.1	0.2	0.5

Table 3.13
Mental Wellness Model C summary statistics.

Parameter	Estimate	Est. Error	l-95% CI	u-95% CI
Intercept[1]	-4.6	0.9	-6.3	-2.7
Intercept[2]	-2.0	0.9	-3.8	-0.2
Intercept[3]	0.9	0.9	-0.9	2.7
Intercept[4]	4.5	0.9	2.7	6.4
Bike share	1.0	0.2	0.6	1.4
Exclusive	-0.4	0.4	-1.2	0.4
log(Shared Micromobility Use (minutes per day))	0.3	0.1	0.2	0.5
Female	-0.3	0.3	-0.9	0.3
Income $50k to $100k	-0.5	0.4	-1.3	0.3
Income $100k to $150k	0.2	0.5	-0.7	1.1
Income More than $150k	-0.7	0.4	-1.6	0.1
Age 35 to 55	0.3	0.3	-0.3	0.9
Age Over 55	1.1	0.5	0.1	2.2
White	0.3	0.3	-0.3	1.0

Table 3.14
Mental Wellness Model D summary statistics.

Parameter	Estimate	Est. Error	l-95% CI	u-95% CI
Intercept[1]	-5.8	1.0	-7.8	-3.8
Intercept[2]	-3.3	1.0	-5.2	-1.3
Intercept[3]	-0.3	1.0	-2.2	1.7
Intercept[4]	3.4	1.0	1.5	5.4
Bike share	0.9	0.2	0.5	1.3
Exclusive	-0.5	0.4	-1.3	0.4
log(Shared Micromobility Use (minutes per day))	0.1	0.1	-0.1	0.3
Female	-0.3	0.3	-1.0	0.3
Income $50k to $100k	-0.6	0.4	-1.4	0.3
Income $100k to $150k	0.2	0.5	-0.7	1.1
Income More than $150k	-0.9	0.4	-1.7	0.0
Age 35 to 55	0.2	0.3	-0.5	0.8
Age Over 55	1.0	0.6	-0.1	2.2
White	0.2	0.3	-0.5	0.9
First used 6 months to a year ago	-0.4	0.5	-1.4	0.6
First used Less than 6 months ago	-0.7	0.5	-1.7	0.3
First used More than 2 years ago	0.2	0.3	-0.4	0.9
Frequency Never	-0.9	1.3	-3.5	1.6
Frequency Less than one trip a month	-2.4	0.5	-3.5	-1.4
Frequency 1 to 3 trips a month	-0.9	0.4	-1.8	-0.1
Frequency 1 to 2 trips a week	-0.9	0.4	-1.6	-0.2
Frequency 3 to 4 trips a week	-0.1	0.3	-0.8	0.6

Table 3.15
Mental Wellness Model E summary statistics.

Parameter	Estimate	Est. Error	l-95% CI	u-95% CI
Intercept[1]	-6.1	1.0	-8.1	-4.0
Intercept[2]	-3.5	1.0	-5.4	-1.5
Intercept[3]	-0.4	1.0	-2.4	1.6
Intercept[4]	3.3	1.0	1.4	5.3
Bike share	0.9	0.2	0.5	1.3
Exclusive	-0.6	0.4	-1.4	0.3
log(Shared Micromobility Use (minutes per day))	0.1	0.1	-0.1	0.3
Female	-0.4	0.3	-1.1	0.3
Income $50k to $100k	-0.6	0.4	-1.4	0.3
Income $100k to $150k	0.3	0.5	-0.7	1.3
Income More than $150k	-0.9	0.5	-1.8	0.0
Age 35 to 55	0.1	0.3	-0.6	0.8
Age Over 55	0.7	0.6	-0.4	1.9
White	0.2	0.4	-0.5	0.9
First used 6 months to a year ago	-0.4	0.5	-1.5	0.6
First used Less than 6 months ago	-0.6	0.5	-1.7	0.5
First used More than 2 years ago	0.3	0.4	-0.4	1.0
Frequency Never	-0.8	1.3	-3.4	1.9
Frequency Less than one trip a month	-2.5	0.5	-3.6	-1.5
Frequency 1 to 3 trips a month	-1.1	0.4	-1.9	-0.2
Frequency 1 to 2 trips a week	-1.0	0.4	-1.7	-0.2
Frequency 3 to 4 trips a week	-0.1	0.4	-0.8	0.6
Mean Weighted Average Absolute Grade	0.2	0.2	-0.2	0.5
Mean Proportion Residential	0.0	0.2	-0.4	0.3
Mean Weighted Average Number of Lanes	-0.2	0.2	-0.6	0.1
Mean Relative Humidity (2 m)	-0.2	0.3	-0.7	0.4
Mean Precipitation	0.8	0.3	0.2	1.4
Mean Wind Speed (10 m)	0.2	0.2	-0.3	0.7
Mean Weighted Average Absolute Grade:Mean Proportion Residential	0.1	0.2	-0.3	0.4
Mean Weighted Average Absolute Grade:Mean Weighted Average Number of Lanes	0.0	0.2	-0.3	0.3
Mean Proportion Residential:Mean Weighted Average Number of Lanes	-0.3	0.2	-0.7	0.0
Mean Relative Humidity (2 m):Mean Precipitation	-0.5	0.6	-1.7	0.8

Parameter	Estimate	Est. Error	l-95% CI	u-95% CI
Mean Relative Humidity (2 m):Mean Wind Speed (10 m)	-0.3	0.3	-0.9	0.3
Mean Precipitation:Mean Windspeed	0.9	0.4	0.2	1.6
Mean Weighted Average Absolute Grade:Mean Proportion Residential:Mean Weighted Average Number of Lanes	-0.1	0.1	-0.3	0.2
Mean Relative Humidity (2 m):Mean Precipitation:Mean Wind Speed (10 m)	-0.9	0.7	-2.4	0.6

Table 3.16
Mental Wellness Model F summary statistics.

Parameter	Estimate	Est. Error	l-95% CI	u-95% CI
Intercept[1]	-5.7	1.0	-7.7	-3.7
Intercept[2]	-3.2	1.0	-5.2	-1.2
Intercept[3]	-0.2	1.0	-2.2	1.8
Intercept[4]	3.5	1.0	1.5	5.6
Bike share	0.9	0.2	0.5	1.4
Exclusive	-0.5	0.4	-1.3	0.3
log(Shared Micromobility Use (minutes per day))	0.1	0.1	-0.1	0.3
Female	-0.4	0.3	-1.0	0.3
Income $50k to $100k	-0.5	0.4	-1.4	0.3
Income $100k to $150k	0.2	0.5	-0.6	1.2
Income More than $150k	-0.9	0.5	-1.7	0.0
Age 35 to 55	0.1	0.3	-0.5	0.8
Age Over 55	1.0	0.6	-0.1	2.1
White	0.2	0.3	-0.5	0.9
First used 6 months to a year ago	-0.4	0.5	-1.5	0.6
First used Less than 6 months ago	-0.6	0.5	-1.7	0.4
First used More than 2 years ago	0.2	0.3	-0.5	0.9
Frequency Never	-0.9	1.3	-3.5	1.6
Frequency Less than one trip a month	-2.5	0.5	-3.5	-1.4
Frequency 1 to 3 trips a month	-1.0	0.4	-1.8	-0.1
Frequency 1 to 2 trips a week	-0.9	0.4	-1.6	-0.2
Frequency 3 to 4 trips a week	-0.1	0.3	-0.8	0.6
Dry Weather	0.3	0.4	-0.4	1.0
Humid and Windy Weather	-0.1	0.5	-0.9	0.8
More Residential	0.1	0.4	-0.6	0.8

4 Modeling Users' Perceived Effects of Shared Micromobility on Safety

4.1 Introduction

Safety plays a critical role in whether people choose active travel and shared micromobility. Objective safety measures capture dimensions of risk, such as crashes or characteristics of the travel environment. Perceived safety, on the other hand, describes how users feel about a mode of travel or the environments in which they ride. As Shamsudin and Hassim (2023) found, the perceived safety of shared micromobility is critical to a person's decision to use shared micromobility. Therefore, more research is needed to understand what influences people's perceived safety of shared micromobility services, so that the factors that improve their perceived safety can be identified. Improving the perceived safety of these services is necessary to increase their ridership, and improvements to the built environment to improve the objective safety will be more politically salient as ridership increases.

It is apparent that streets in the United States are increasingly dangerous to all its users, especially those outside of a vehicle. What is less clear is how safe do people perceive traveling on these streets to be. Research has shown that people traveling on bikes and scooters feel safer when they have dedicated, protected infrastructure. More recent work into shared micromobility has found that people perceive bike share as safer than scooter share. We know less about whether this perceived safety of shared micromobility can be improved with more exposure to using these systems.

In this chapter, I evaluate the perceived safety of shared micromobility, including bike share and scooter share, across the United States. I am interested in understanding if whether the increased use of shared micromobility results in users perceiving these services to be safer. Using the results of the American Micromobility Panel (AMP) project (Fitch et al., 2023), I linked safety perceptions towards shared micromobility with trips taken using these shared micromobility services across the United States. By modeling users' perceived safety of shared micromobility as a function of their use of shared micromobility, their personal characteristics, and their exposure to the built environment and the weather during their trips, I can explore the contributions of these characteristics and experiences to users' perceived safety of these systems. These results help clarify what influences how users of shared micromobility perceive the safety of riding bike share and scooter share and highlight opportunities for improving urban travel environments.

4.2 Literature Review

Traveling on roadways in the United States has become increasingly deadly, with about a 25% increase in traffic fatalities in 2023 compared to 2013 (TRIP, 2024), for a total of 40,990 fatalities in 2023 alone (National Center for Statistics and Analysis, 2024). While pedestrian deaths on roadways in the United States had been declining from the late 1970s through 2011, the period between 2012 and 2016 saw a reversal of this trend (Schneider, 2020). Countries in Europe have been reducing their pedestrian and bicycling injury and fatality rates at a steadier rate than the United States, where the reduction began to slow in the early 2000s (Buehler and Pucher, 2017). In 2018, pedestrian fatality rates per kilometer walked in the United States were 5-10 times higher, and cyclist fatality rates per kilometer cycled were 4-7 times higher than in the United Kingdom, Germany, Denmark, and the Netherlands (Buehler and Pucher, 2021). Meanwhile, the other four nations saw significant declines in fatalities per capita compared to their rates in 1990 and compared to the United States.

The poor safety statistics for those walking and bicycling on roads in the United States are especially concerning as micromobility has become increasingly popular. In addition to bicycles, recent years have seen the introduction of electric bicycles (e-bikes) and electric scooters (e-scooters), changing the landscape of the urban transportation networks in the United States, which has historically been dominated by high levels of vehicle ownership (Paul and Blumenberg, 2023). People living in cities now also have the option to rent bicycles, e-bikes, or e-scooters within shared micromobility systems, exposing people to active travel modes (walking, bicycling, and scooting) without needing to purchase their own device. According to the North American Bikeshare & Scootershare Association (2024), there were at least 172 million shared micromobility trips made in North America just in the year 2023, which is an increase over previous years, 64% of which were on either e-bikes or e-scooters.

Unfortunately, the rise in shared micromobility use has been accompanied by an increase in injuries. Locke et al. (2025) found that traffic injuries involving e-bikes have continued to rise, especially since the COVID-19 pandemic. They also found that 30% of these injuries included a motor vehicle, and 10% of patients needed to be hospitalized. However, because e-bikes and e-scooters are relatively new, researchers are still working to determine how injuries from riding e-bikes compare to similar modes like conventional bicycles. In the Netherlands, Verstappen et al. (2021) surveyed patients in the hospital emergency department who had experienced a crash on their bicycle or e-bike and found no difference in the injuries between the modes. On the other hand, while Verstappen et al. (2021) and Spörri et al. (2021) found that the riders of e-bikes were generally older and Verstappen et al. (2021) found they had higher rates of comorbidities than riders of conventional bicycles, Goodman et al. (2023) have identified e-bikes as a pediatric health problem in the United States where they observed an increase in hospitalizations of children in recent years from e-bike use. More than 60% of both bicycle and e-bike injuries included head injuries. However, one difference between bicycle injuries from e-bike injuries is that thoracic injuries (injuries to the chest area) were more prevalent for conventional bicycle riders, and e-bike riders had higher rates of pelvic injuries that were comparable with motorcycle injuries (Spörri et al., 2021). Traumatic brain injuries were also found to not differ between conventional bicycles and e-bikes and instead were more dependent on other factors such as speed or alcohol consumption (Verbeek et al., 2021). Although riders of e-bikes can easily travel much faster than riders of conventional bicycles, and while these speeds may be comparable to smaller or slower conventional motorcycles, Spörri et al. (2021) found that the injuries of e-bike riders resemble the injuries of riders of conventional bicycles, and not the injuries of motorcycle riders. This suggests that, while the speeds and ease of acceleration invoke comparisons to motorcycles, e-bikes may not pose the same risks of injury and death as motorcycles.

E-scooters, while newer than e-bikes, are showing similar signs of increased injury rates compared to their non-electric counterparts. In Australia, about one third of fatalities of e-scooter riders were children between 2020 and 2025, which was a higher rate than adult riders (Haghani, 2025). Toofany et al. (2021) identified trends a lack of helmet usage in their systematic review, and they also noted that some literature has found e-scooter injuries to be more severe than non-motorized scooters and similar modes. These results highlight a worry that research and policymaking around e-scooters is lagging too far behind the clear increased risks associated with using the devices. A recent systematic review of existing research on injuries from riding e-scooters across more than 5,000 patients, multiple hospitals, and multiple countries found that the most common injury was upper limb fractures along their arms, compared to more severe injuries like concussions or traumatic brain injuries, which were rarer (3.2% and 2.5%, respectively) (Singh et al., 2022). They also found that injuries were most common for young, white males. Overall, males were about 60% of the injured patients, and the average age was about 33. This contrasts with prior research for e-bike injuries, which found injuries to be more common for older users. This suggests that user demographics may play an important role in their objective and perceived safety. Perceived safety helps determine their use of shared micromobility, and therefore exposure to risk, rather than their age determining users' risks of injury while riding.

In response to the safety risks active travel users face on streets also occupied by motor vehicles, safety interventions are implemented to adjust the designs of streets to better accommodate those walking, bicycling, scooting, skating, etc. DiGioia et al. (2017) conducted a literature review of the infrastructure impacts on bicycle safety and found that bicycle lanes in general are beneficial for the safety of the bicyclists and may reduce collisions but are not always statistically significant. More infrastructure treatments like bicycle boulevards and cycle tracks can also reduce crash rates. However, the authors note that despite recent increases in research on this topic, there are still significant gaps in the literature characterizing the safety improvements of infrastructure treatments for bicyclists. Tian et al. (2022) found that e-scooter riders identified bicycle lanes as increasing their protection. While e-scooters were found to be easier to steer than bicycles (Dozza et al., 2022), e-scooters have been found to be more difficult to slow or stop than bicycles, so additional safety precautions may be needed to improve the safety for e-scooters if they are unable to stop safely in more challenging bike lane geometries (Dozza et al., 2023).

Beyond infrastructure, the safety of bicycling and scooting is addressed inconsistently through a patchwork of local and regional policies and operator guidelines for safe use (Pimentel et al., 2020). Unlike with driving, people using active transportation modes do not have a uniform set of rules to follow wherever they travel to promote safe behavior. Device operators have various strategies to encourage safer behavior when using shared micromobility devices, such as presenting safety tips on the bike share bicycles or within the app, reminding users of local policies in the app, identifying safe infrastructure within the app, requiring safety verification before use (such as answering questions), or even offering benefits for proof of helmet use with user submitted photos (Fischer, 2020). However, operators have limited ability to enforce safe behavior, such as helmet use, and beyond geofencing and limiting maximum speeds of the devices, they also lack control over how the devices are used.

Another aspect of the safety of shared micromobility is how users or potential users perceive the safety of riding bike share and scooter share. Christ et al. (2023) reviewed the literature on bicycling and safety and identified the need for more research into the perceived safety of bicycling and concluded that researchers have not adequately bridged the gap between objective measures and perceived measures of safety. Micromobility users when surveyed responded feeling safer riding within protected infrastructure, and less safe when riding near vehicles (Fonseca-Cabrera et al., 2021). Tzouras et al. (2024) found that e-scooters were perceived to be less safe than e-bikes, and that females perceived both to be more unsafe than males did. It is important to document these perceived safety concerns as researchers, as it provides a roadmap for encouraging potential riders of shared micromobility to try these services. This study contributes to this gap by examining how users perceive the safety of riding shared micromobility, and how their use of bike share and scooter share, their environment, and their sociodemographic characteristics affect these perceptions.

4.3 Methodology

4.3.1 Study Design

During Summer 2022, participants completed a travel diary for all their trips across every mode, and then participants were invited to complete a post diary survey later in the summer to answer questions about shared micromobility and their experiences during the study period (see Section 2.1 The American Micromobility Panel Project for details). This was possible using survey and travel diary data of micromobility users across various cities in the United States collected during Summer 2022 as part of the AMP project. In the survey included within the AMP project, participants were asked if they felt bike share and scooter share were unsafe and if they worried about crashing while riding bike share and scooter share. With these questions, I am interested in understanding how a person's shared micromobility use influences their perceived safety of using shared micromobility.

4.3.2 Model Descriptions

To evaluate the perceived safety of using shared micromobility, the results from four post-diary survey questions representing dimensions of shared micromobility safety were modeled as a function of participants' characteristics, their use of shared micromobility, and their exposure to the built environment and weather. Perceived safety was modeled given that it is an important component of users' experiences with shared micromobility. The two dimensions of perceived safety that were measured were *unsafe* and *worry crashing* for both bike share and scooter share, and they are described in Table 4.1.

Table 4.1
Description of the response variable for the safety model.

Safety Dimension	Survey Question
Unsafe	Bike-share is unsafe
	Scooter-share is unsafe
Worry Crashing	I worry about crashing a bike-share bike
	I worry about crashing a scooter-share e-scooter

Responses are on the following Likert scale:
Strongly disagree, *Disagree*, *Neither agree nor disagree*, *Agree*, *Strongly agree*

Given that each participant could answer a question for each dimension of safety for both bike share and scooter share, the four Likert scale responses about users' perceived safety of riding shared micromobility were reorganized such that each mode-dimension response was placed on a separate row in a single response variable. This is possible due to the wording of each of the four questions having the same order and level of response options, where *Strongly disagree* is the most positive response towards the safety of riding shared micromobility and *Strongly agree* is the most negative response. Each observation in the response variable is a Likert response based on a dimension of safety (the micromobility mode is unsafe or the respondent worries about crashing the micromobility mode), by mode (bike share or scooter share), and by person. The observed Likert scale responses were modeled using a generalized ordinal logistic regression model because of the ordinal nature of the response variable.

The predictor variables were selected to capture information about the participant that may affect their perceived safety of shared micromobility. These include variables such as the participant's *city* of residence (the city in which they were recruited for the AMP study), which is the primary way to represent the unobserved characteristics of the participant's environment of their shared micromobility use in the model, and income to represent their sociodemographic characteristics. Perceptions of shared micromobility may differ by sociodemographic characteristics such as *income*. Including a participant's *income* category served as a proxy of a participant's characteristics (e.g., education level, employment status, homeownership, etc.) that may influence their baseline responses about shared micromobility use. Observations in the data are identified by *mode* – if they are about bike share or scooter share – and if the participant is an *exclusive* user of either bike share or scooter share or a non-exclusive user of shared micromobility modes. These distinctions are important for several reasons. Bike share use and scooter share use can differ by trip purpose and by trip length. Bike share and scooter share also require different skills to operate, such as knowing how to ride a bicycle to ride a bike share bike.

Users are expected to be more comfortable with shared micromobility use if they use both modes, as opposed to those who exclusively use one mode and who may be less familiar with these systems. Both *mode* and *exclusive* are included as predictors in the model. Additionally, each participant's *shared micromobility use* is included (i.e., the general use of each shared micromobility mode in total trip duration per survey days), which is the primary predictor of interest based on my hypothesis.

Each participant has a unique *shared micromobility use* value in units of minutes per day to represent their total exposure for each shared micromobility mode that they used. I reasoned that shared micromobility use may relate to the response variable partly through several unmeasured psychological latent variables, such as experience, comfort, and skill, which were captured in my analysis with their shared micromobility use variable. My conceptual model with the response variable and all the predictor variables included with the model are displayed in Figure 4.1.

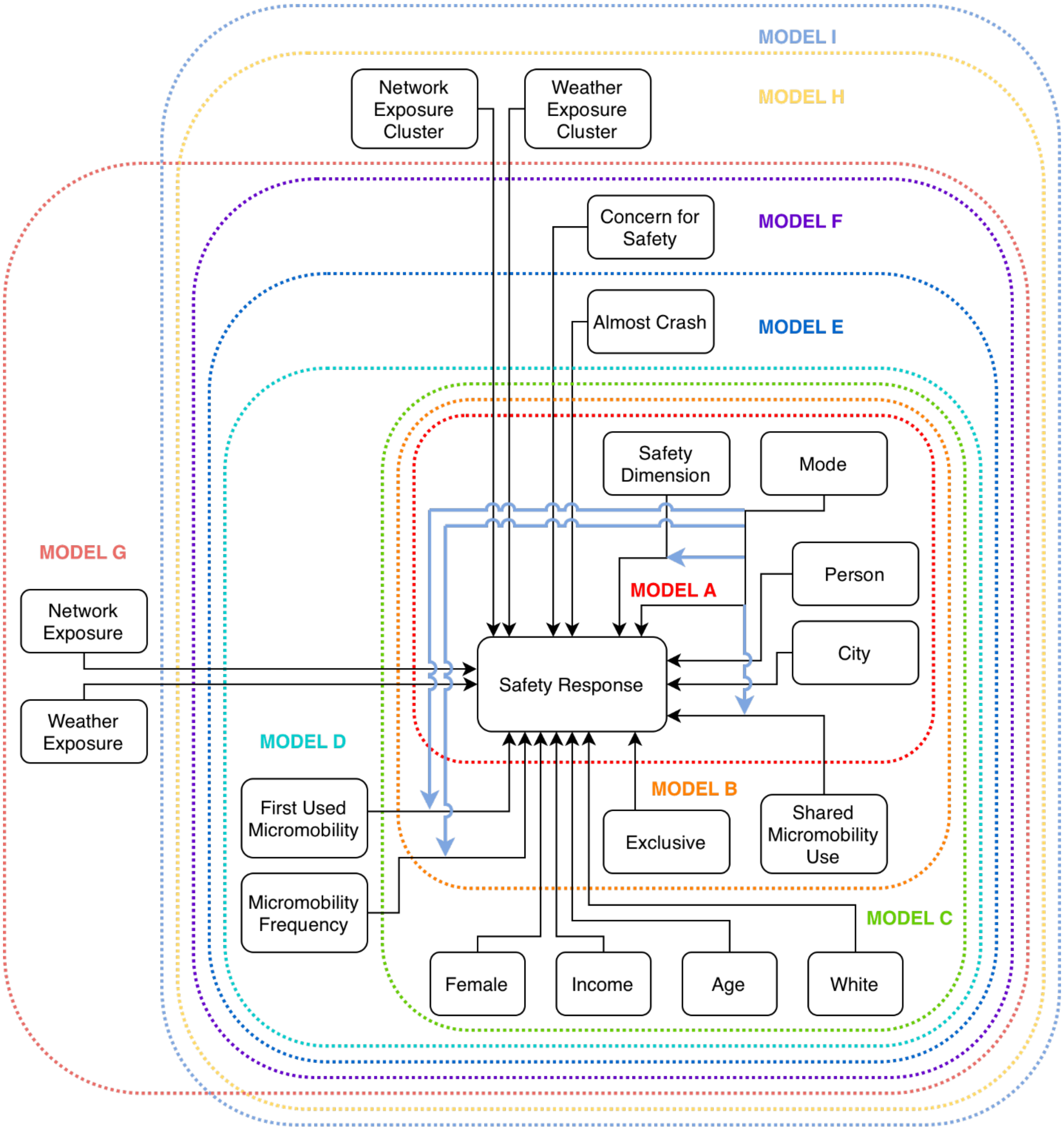

Figure 4.1
Diagram of the safety conceptual model, with interactions with *Mode* introduced in Model I.

4.3.3 Data Summaries

The results of the post-diary survey questions for the two safety related questions that are used to create the safety response variable are displayed in Figures 4.2 and 4.3. As shown in

Figure 4.2, users are more likely to disagree than agree that bike share or scooter share are unsafe. Very few users agreed that bike share and scooter share are unsafe, and agreement was the least popular responses. Most disagreed, and there were more users that were neutral than in agreement that bike share and scooter share were unsafe. Out of those who disagreed that bike share and scooter share were unsafe, just under half, a significant portion, strongly disagreed. Between bike share and scooter share, users were more likely to feel that scooter share is unsafe compared to bike share, were more neutral that scooter share was unsafe compared to bike share and disagreed less that scooter share was unsafe compared to bike share. From these responses, users in our study did not feel that riding bike share or scooter share is unsafe, and they felt that bike share was safer in general compared to scooter share.

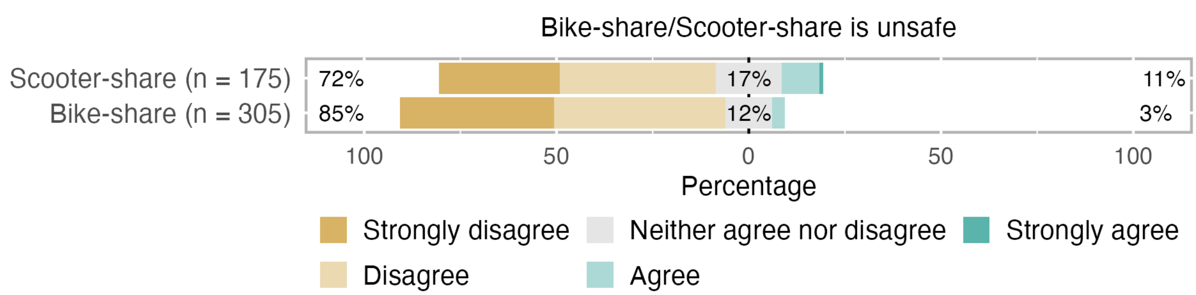

Figure 4.2
Users' perception of bike share or scooter share being unsafe.

Respondents mostly disagreed that they worry about crashing a bike share bike or scooter share scooter (Figure 4.3). However, more than a quarter of users agreed that they worried about crashing a scooter share scooter, about 10 percentage points more than for bike share bikes. This is a marked difference in agreement for worrying about crashing compared to feeling that bike share or scooter share is unsafe, which suggests that even if some users feel they might crash, they do not interpret that to the mode being unsafe to use. For users of micromobility, the safety of a mode may not always include the worry about crashing.

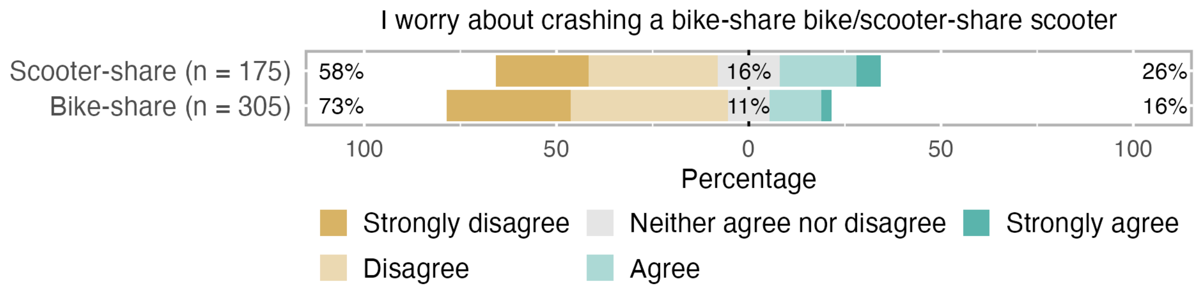

Figure 4.3
Users' perception of worrying about crashing a bike share bike or scooter share scooter.

The stronger and more negative responses towards bike share being unsafe compared to scooter share may be impacted by the distribution of bike share users compared to scooter share users in the respondents. Table 4.2 shows the summary of the participants' characteristics in the data for the models. Each of these characteristics are a predictor. The participants are mostly balanced among *income* categories, over half are younger than 35 years, two thirds are not *Female*, and nearly three-quarters identify as *White*. Additionally, most participants in the model data only used one of the shared micromobility modes, and not both bike share and scooter share as shown by *Exclusive Users*.

Table 4.2
Summary of the participant characteristics used in the analysis.

Characteristic	Percentage (n = 427)
Exclusive Users	85.7
Female	34.0
White	74.5
Age Under 35	52.9
Age 35 to 55	38.4
Age Over 55	8.7
Income Less than $50k	23.9
Income $50k to 100k	28.3
Income $100k to 150k	19.4
Income More than $150k	28.3

Additionally, participants mostly reported that their travel choices are affected by their concern for their safety (Table 4.3). Participants were about evenly split between rating their concern for safety as *Moderately important* and *Extremely important*, but they were most likely to rate it as *Very important*. This variable was included in the model because participants generally reported that their concern for their safety influences their travel choices, although the importance they place on safety varies across individuals. I expected that their concern for safety would help inform how they perceive the safety of riding shared micromobility.

Table 4.3
Summary of the participants' travel choices affected by their concern for safety.

Importance	Percentage (n = 427)
Not at all important	3.3
Slightly important	9.6
Moderately important	26.9
Very important	36.3
Extremely important	23.9

I also expected that participants' frequency of almost crashing would influence how they perceive the safety of shared micromobility. According to Table 4.4, participants overwhelmingly report *Never or almost never* crashing (86.2%). Most of the other participants who do almost crash report doing so *Less than one quarter of my trips*. Possible explanations include that participants may be experienced riders of shared micromobility who rarely feel they lose control of their vehicle, that they have access to safe infrastructure protecting them from other riders and vehicles, that they are less aware of situations in which they did almost crash, or some combination of these factors. This result is not too surprising considering how unlikely they are to worry about crashing (Figure 4.3) or to think that shared micromobility is unsafe (Figure 4.2).

Table 4.4
Summary of how often participants report almost crashing.

Frequency	Percentage (n = 427)
More than half of my trips	0.7
Between one quarter and half of my trips	0.7
Less than one quarter of my trips	12.4
Never or almost never	86.2

The recruitment process for the AMP study generally favored more frequent users of shared micromobility, so I expected that the participants would generally be experienced riders (Table 4.5). Most participants for both bike share and scooter share first used the services *more than 2 years ago*, and a small portion of them only just first used the services within a year before the study. In general, we can expect that a participant has more experience with bike share than with scooter share, considering that they have a higher proportion of first using them *more than 2 years ago* and that scooter share services tend to be newer than bike share services in the United States. This may also be related to why participants disagreed more that bike share was unsafe compared to scooter share (Figure 4.2). They may have also been less worried about crashing bike share than scooter share (Figure 4.3) if they might have had more exposure to riding bike share than scooter share.

Table 4.5
Percentage of when each participant first used bike share and scooter share.

First Used	Bike share (n = 305)	Scooter share (n = 175)
Less than 6 months ago	7.2	15.4
6 months to a year ago	6.9	10.3
1 to 2 years ago	15.7	22.9
More than 2 years ago	70.2	51.4

In addition to having a longer history with bike share than scooter share, respondents also tended to use bike share more frequently than they did scooter share (Table 4.6). Considering that respondents generally had more experience with bike share than with scooter share, it is not surprising that they might feel more comfortable to use bike share more frequently than scooter share, with two-thirds of bike share respondents using the service at least three times per week compared to under half of scooter share respondents.

Table 4.6
Percentage of how often each participant reported they used bike share and scooter share.

Frequency	Bike share (n = 305)	Scooter share (n = 175)
Never	0.0	1.7
Less than one trip a month	4.6	9.7
1-3 trips a month	9.8	21.1
1-2 trips a week	18.7	21.7
3-4 trips a week	21.0	16.6
5+ trips a week	45.9	29.1

In addition to participants having reported using bike share more frequently and for a longer period, they were also observed from their trips to use bike share for more minutes per day than scooter share (Table 4.7). If they are mostly only taking one round trip per day, this would suggest that our participants were using bike share for longer trips than for scooter share. This makes for an interesting finding that even if they have more exposure using bike share, they still might perceive it to be safer despite more exposure to the environment and more potential for crashes.

Table 4.7
Summary of each participants' use of bike share and scooter share in minutes per day.

Mode	Mean	SD
Bike share	10.69	11.71
Scooter share	5.95	8.98

Participants mostly experienced relatively humid micromobility trips with lower windspeeds and little precipitation. The street segments they traveled on were not very steep and mostly had two to three lanes (Table 4.8).

Table 4.8
Summary of each participants' exposure to the environment.

Variable	Mean	SD
Mean Weighted Absolute Average Grade	0.014	0.009
Mean Weighted Average Number of Lanes	2.558	0.599
Mean Proportion Residential	0.163	0.189
Mean Relative Humidity (2 m)	70.146	14.325
Mean Precipitation	0.110	0.297
Mean Windspeed (10 m)	12.743	6.010

Table 4.9 shows the percentage of participants based on which city they were recruited in. As noted earlier, while the AMP study attempts to cover a large number of shared micromobility markets, some of these cities have very few participants who completed the post-diary survey. If they did not complete the post-diary survey, then they cannot be included in this research (because we do not know how they perceive the safety of shared micromobility).

Table 4.9
Summary of which cities participants were recruited in.

City	Percentage of Participants (n = 427)
Atlanta, GA	1.4
Austin, TX	1.4
Baltimore, MD	0.9
Berkeley, CA	2.1
Charlotte, NC	1.2
Chicago, IL	16.6
Columbus, OH	2.1
Denver, CO	6.1
Detroit, MI	0.2
Fort Collins, CO	0.2
Grand Rapids, MI	0.5
Indianapolis, IN	0.5
Long Beach, CA	2.1
Los Angeles, CA	4.0
Louisville, KY	0.5
Minneapolis, MN	4.2
Nashville, TN	0.2
Norfolk, VA	0.2
New York, NY	14.8
Pittsburgh, PA	0.2
Portland, OR	4.7
Providence, RI	1.4
Reno, NV	0.2
Sacramento, CA	1.4
Salt Lake City, UT	0.5
San Diego, CA	0.5
San Francisco, CA	12.2
San Jose, CA	1.6
Seattle, WA	0.9
Spokane, WA	0.5
Tampa, FL	0.7
Washington, D.C.	15.9

From Figure 4.4, there are no obvious patterns in the types of facilities participants used for their shared micromobility trips. They mostly traveled on segments with lower grades (not as steep), less residential segments (possibly more urban), and with a wider distribution of lanes between two and four lanes.

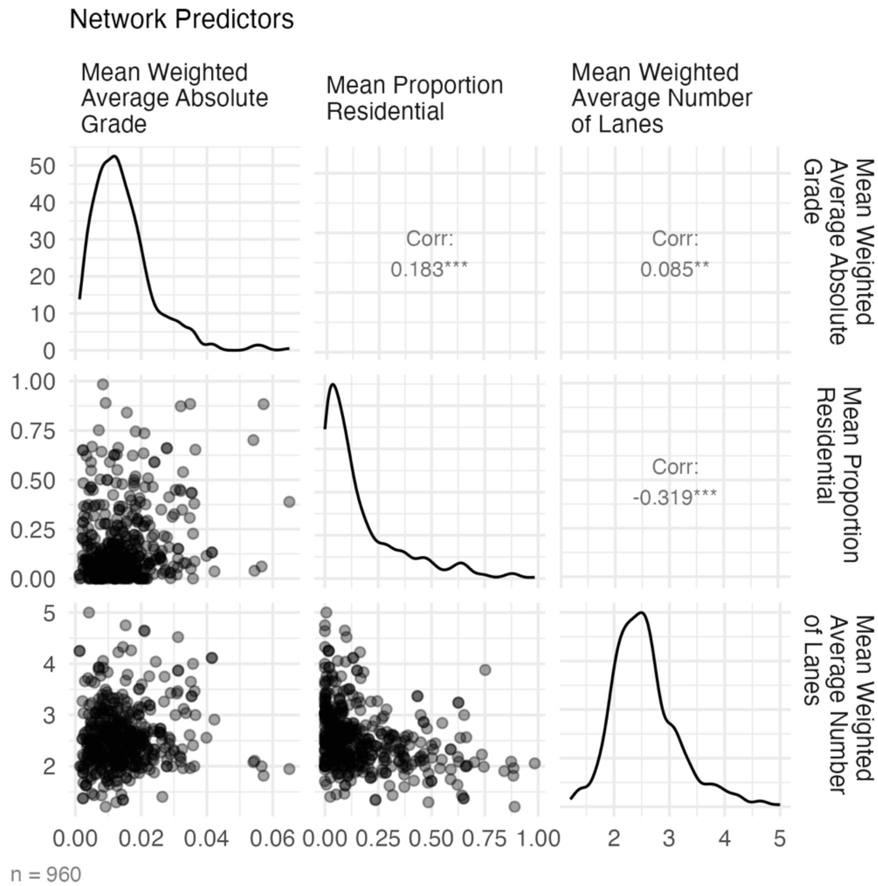

Figure 4.4
Distributions of the network variables in the models.

Figure 4.5 demonstrates that precipitation events were rare during the shared micromobility trips by the participants in the model data, but that humidity and wind were less uniform across the data. It is possible that humidity and wind may vary across participants, and therefore their responses toward the effects of using shared micromobility.

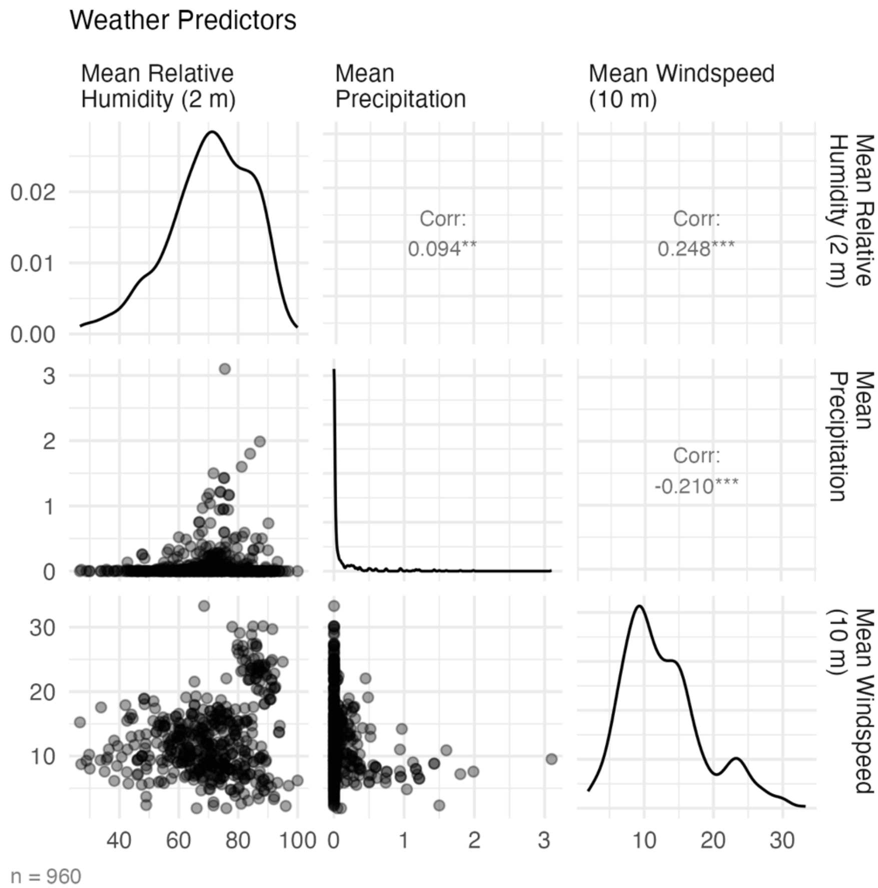

Figure 4.5
Distributions of the weather variables in the models.

I expected that across the network variables and across the weather variables, there would be noisy observations that would make the modeling more challenging and obscure the interpretation of the results. Therefore, I used clustering techniques to create two predictors by grouping individuals into network clusters based on the three network exposure variables and into weather clusters based on the three weather exposure variables. I expected that membership in discreet categories would better describe network or weather exposure throughout participants' shared micromobility trips than the individual variables do. The observations are noisy, and clustering helps to reduce the model's sensitivity to the noise. Clustering makes it easier to describe the effects of these exposures on participants' perceived safety of micromobility (e.g., exposure to wind and high humidity during trips compared to trips during dry weather with no wind).

The network exposure cluster and weather exposure cluster were created with k-means clustering. I used both the Elbow Method and the Silhouette Analysis to select the number of clusters based on their performance metrics. Both methods iterate over an increasing number of clusters and output a performance metric. The Elbow Method evaluates the total within-clusters sum of squares – the total of all squared distances between each cluster centroid and the observations within each cluster. The total within cluster sum of squares will decrease as the number of clusters increases. An ideal number of clusters would be located at an "elbow" in the plot of number of clusters against the total within cluster sum of squares. This elbow would identify where further increasing the number clusters does not provide as much benefit as the last increase. The Silhouette Analysis calculates the average distance between the observation and every other observation within its cluster and the average distance between the observation and observations in the neighboring cluster (a silhouette ranging from -1 to 1) to quantify if each observation is appropriately placed in a cluster with each selected number of clusters. The larger the silhouette, the better the classification for that observation. The number of clusters that performs best based on the Silhouette Analysis is the one with the highest average silhouette width, which is the average silhouette taken across all observations.

4.3.4 Clustering Based on the Network Variables

According to Figure 4.6, the Elbow Method does not present an obvious "elbow" (sharp change in the curve of plotted total within-cluster SS by number of clusters) that would suggest an ideal number of clusters for the network exposure predictors. Based on the Silhouette Analysis, two clusters have a noticeably higher average silhouette width than having more clusters, which is suggesting that the ideal number of clusters based on the silhouette analysis is two. I chose two clusters given there are only three variables and a limited number of observations in the model data, and it helps the discussion to be more straightforward.

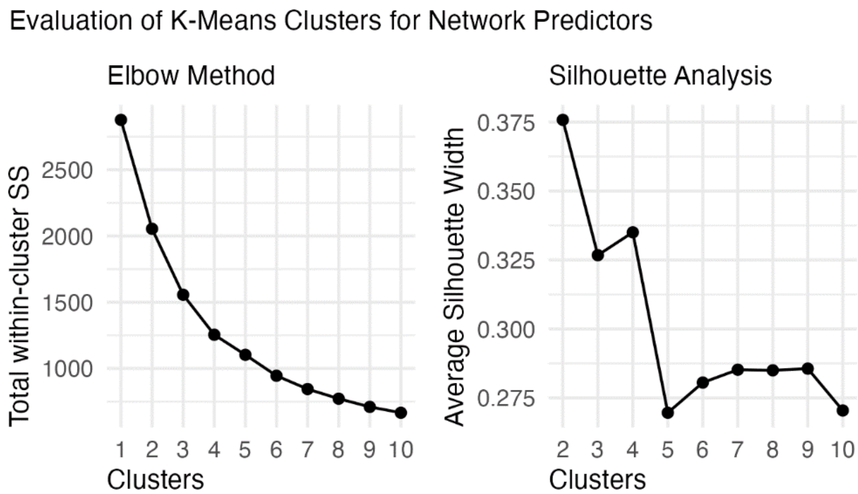

Figure 4.6
Evaluation of the number of k-means clusters for the clustering based on the network predictors.

The result of the k-means clustering based on the network exposure predictors is shown in Figure 4.7. Plotting the data color-coded by the clusters, the two clusters can be identified by the mean proportion of residential segments within the trips. Cluster 1 contains the individuals whose trips are mostly not on residential streets, while Cluster 2 is defined by having higher proportions of residential streets. Cluster 1 and Cluster 2 do not differ much between the mean weighted average absolute grade, but steeper slopes appear in Cluster 2. Similarly, both clusters have a range of average number of lanes, but individuals in Cluster 1 may be more likely to have a higher average number of lanes across their trips. The new network exposure predictor is defined by a cluster named *Less Residential* (Cluster 1) which comprises individuals whose trips are less residential, flatter, and more likely to have a higher number of lanes, and a cluster named

More Residential (Cluster 2) comprising individuals whose trips are more residential with more opportunity for steeper slopes and a lower number of lanes.

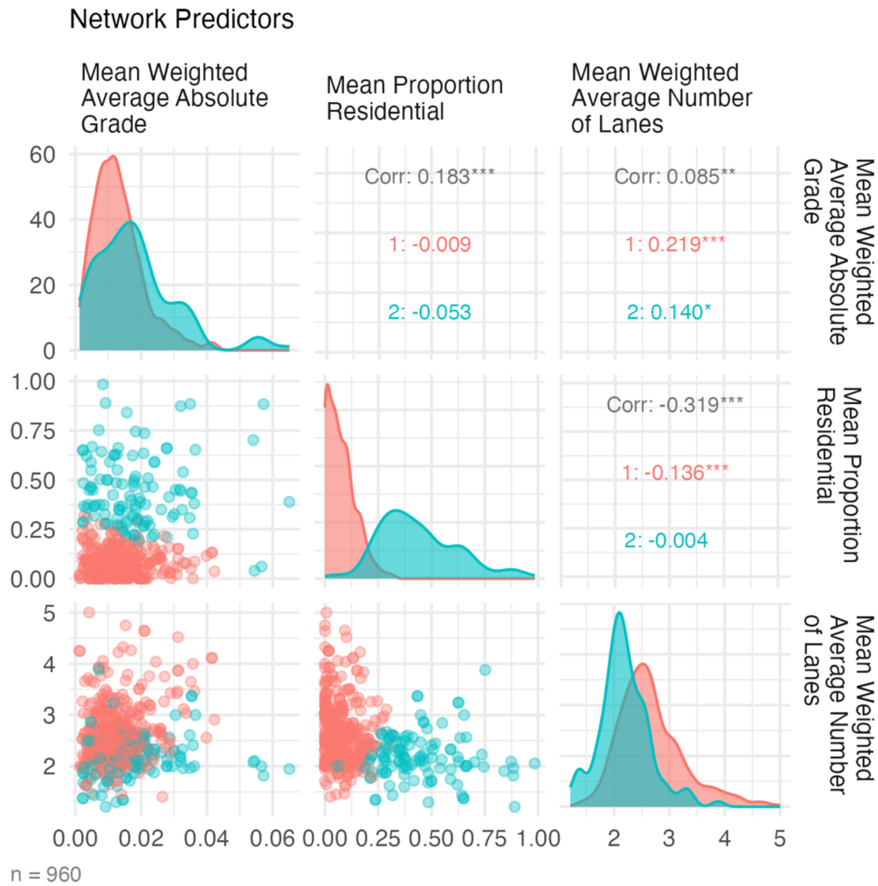

Figure 4.7
Results of clustering participants by the network exposure predictors.

4.3.5 Clustering Based on the Weather Variables

The clustering based on the weather variables followed the same method as described for the network variables. According to Figure 4.8, the Elbow Method does not present an obvious "elbow" (sharp change in the curve of plotted total within-cluster SS by number of clusters) that would suggest an ideal number of clusters for the weather exposure predictors. Based on the Silhouette Analysis, 3 clusters have a noticeably higher average silhouette width than having more clusters, which is suggesting that the ideal number of clusters based on the silhouette analysis is 3. Therefore, 3 clusters may be appropriate for our data. I decided on 3 clusters to keep the clustering simple, considering there are 3 variables with a limited number of observations, and to aid in the interpretation of the effects of the clusters on the response for a meaningful discussion.

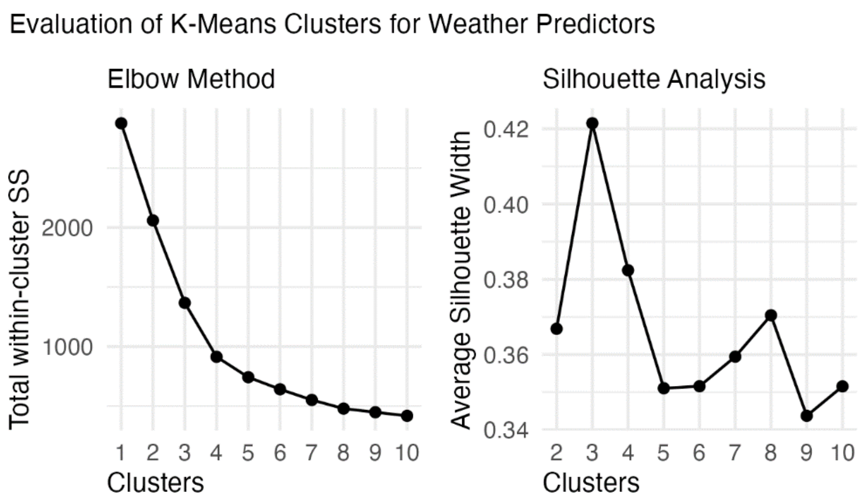

Figure 4.8
Evaluation of the number of k-means clusters for the clustering based on the weather predictors.

Figure 4.9 demonstrates the weather variable data color-coded by the three clusters determined by the k-means clustering algorithm. Clusters 1 and 2 contain the participants who experienced the most humidity. Cluster 1 also includes the individuals with the higher average wind speeds across their trips compared to Clusters 2 and 3. Based on these observations, we can generally consider Cluster 1 to be the *Humid and Windy Weather*, Cluster 2 to be the *Humid and Not Windy Weather*, and Cluster 3 to be the *Dry Weather*. To put it simply, the clustering separated those individuals who had trips with some noticeable weather events (higher wind speeds, precipitation, and humidity) from those with generally fewer or no weather events, and it made a distinction between high average humidity with and without windy conditions.

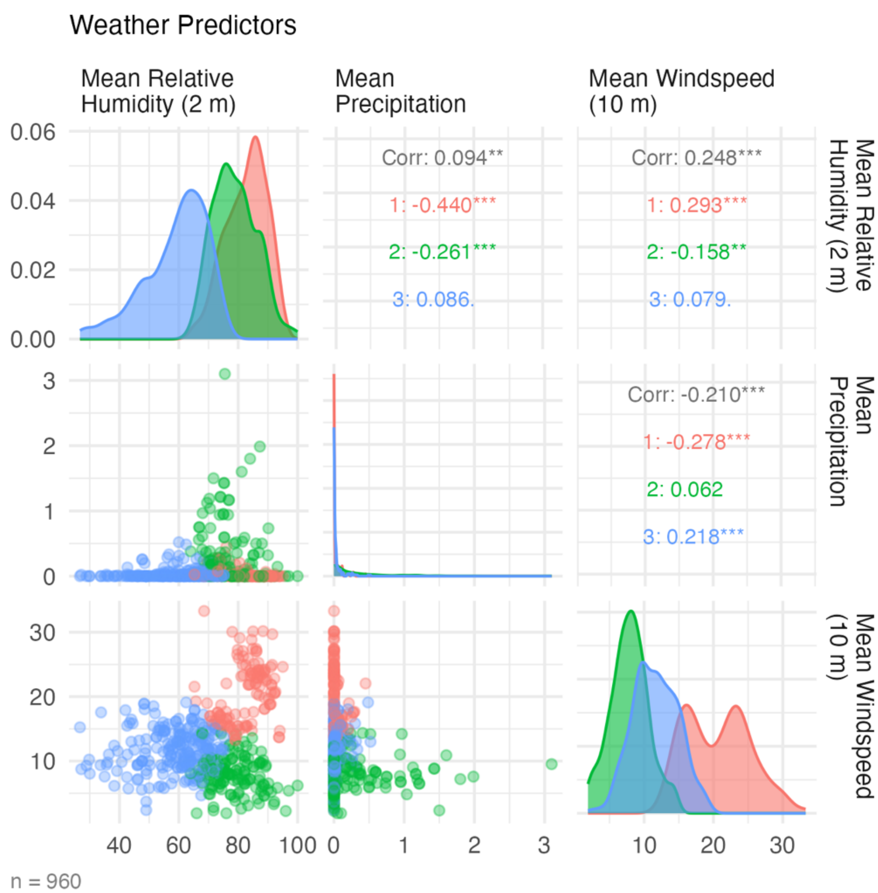

Figure 4.9
Results of clustering participants by the weather exposure predictors.

4.3.6 Model Descriptions

I estimated nine models to evaluate the impacts of the various predictors on the response variable based on the general model described mathematically in the previous section. I began with a simple model, and each subsequent model increases in complexity by introducing a new set of predictors, which are organized thematically by their expected contribution to the model. This stepwise approach allowed me to assess whether the addition of new predictors meaningfully improves the model. A summary of the nine models is shown in Table 4.10. The simplest model, Model A, contains what I considered to be the essential predictors of the analysis: the *safety dimension*, *person*, *city*, and *mode*. *Person* and *city* identify the response at the person-level and city-level, respectively. The *safety dimension* identifies if the Likert-scale response is for *feeling unsafe* or for *worrying about crashing*. *Mode* identifies if the response is about bike share or scooter share. Model B builds upon Model A by introducing objective measures of a respondent's use of shared micromobility with a predictor to determine if the respondent exclusively uses that mode or not, and a predictor that is a measure of how much a respondent uses the shared micromobility mode in minutes per day. Importantly, the predictor for the shared micromobility use is transformed by natural log due to the expected non-linear effect on the response variable – I expect that as a user increases their use of shared micromobility, the effect of the change in daily use from 20 minutes per day to 25 minutes per day would be less than the effect of the change from never using the shared micromobility mode (zero minutes per day) to beginning to use it five minutes per day, even when both changes in use are five minutes per day. Model C builds upon Model B by adding sociodemographic predictors in addition to the baseline predictors and the objective measures of use of shared micromobility. These sociodemographic predictors include whether the respondent is female, is within a certain income bracket, is within a certain age bracket, and is White or not White. Model D builds upon Model C by adding perceived shared micromobility experience based on how long ago a participant thinks they first used the service and perceived shared micromobility use based on how often a participant thinks they use the service. Model E adds a predictor to measure almost crashing on shared micromobility. Model F introduces the post-diary question asking respondents if their concern for safety affects their travel choice to better understand how participants perceive safety, and whether safety is something they think about beyond the time they spend on the shared micromobility device. Model G introduces environmental exposure with the previously described network predictors and weather predictors. Model H includes all the predictors as Model F, except instead of introducing all the environmental exposure predictors, it includes two predictors based on the clustering: one for the clustered network exposure and another for the clustered weather exposure. Model I builds upon Model H by introducing interactions between the mode and mode-based predictors.

Table 4.10
Descriptions of each safety model.

Model	Description
A	Safety Dimension + Person + City + Mode
B	Model A + objective measures of shared micromobility use
C	Model B + sociodemographic predictors
D	Model C + perceived shared micromobility experience and use
E	Model D + almost crash
F	Model E + concern for safety affecting travel choice
G	Model F + environmental exposure predictors
H	Model F + network exposure cluster + weather exposure cluster
I	Model H + interactions between mode and mode-dependent predictors

4.4 Results

The results presented in this section are based on Model H, the large model with the clustered environmental exposures. Based on the LOO CV (Table 4.11), it was the model expected to perform best on new data. Other models, like Models F and E, are not significantly worse performing based on LOO CV and could likely be just as useful of a model as Model H. Overall, Model I is the only model that would perform worse, the rest are very similar in their expected performance. However, Model H retains most of the information in the predictors selected for this analysis without sacrificing prediction performance. Choosing Model H allows us to observe how influential these predictors are on predicting perceived safety of shared micromobility.

Table 4.11
Results of comparing the LOO CV of each safety model.

Model	ELPPM Difference	SE Difference
H	0.0	0.0
F	-0.2	1.8
E	-2.1	2.5
G	-2.6	2.0
A	-4.2	7.0
B	-4.7	6.8
C	-7.0	6.5
D	-9.1	6.0
I	-9.5	3.1

The average rating of a shared micromobility user's perceived safety of shared micromobility is presented in Figure 4.10. The predictors *Bike share Use (minutes per day)* and *Scooter share Use (minutes per day)* were transformed by natural log due to the suspected non-linear effect on the outcome variable. This non-linear – diminishing returns – effect is assumed because conceptually using more shared micromobility is unlikely to cause a linear increase in measures such as changes in the perceived safety of shared micromobility. I present the results for perceived safety as a latent variable scaled between 1 and 5, where the lower the values represent a disagreement that shared micromobility is unsafe, and the higher values represent an agreement. I chose to present the results this way instead of as discrete values because a user's perception of their safety may occupy a spectrum between *Strongly disagree* and *Strongly agree*, and I am more interested in the range of perceived change rather than the specific difference between categories of perceived change in safety. Additionally, as these responses are about their experience using shared micromobility over Summer 2022 as a whole and not by trip, presenting the results on this scale felt more appropriate for a response that would represent an aggregate of their experiences, which is unlikely to be precise and accurate to how they feel about riding shared micromobility on any given trip.

Figure 4.10 shows that bike share is predicted to have more disagreement that it is unsafe on average and scooter share to be more neutral on average. Both are quite uncertain. Also, while I expected diminishing returns in the effect of shared micromobility use, the mean within the interval does not show a strong logarithmic trend. For both modes, the model predicts that perceived safety of shared micromobility will improve with shared micromobility use, just that the improvement will be marginal on average.

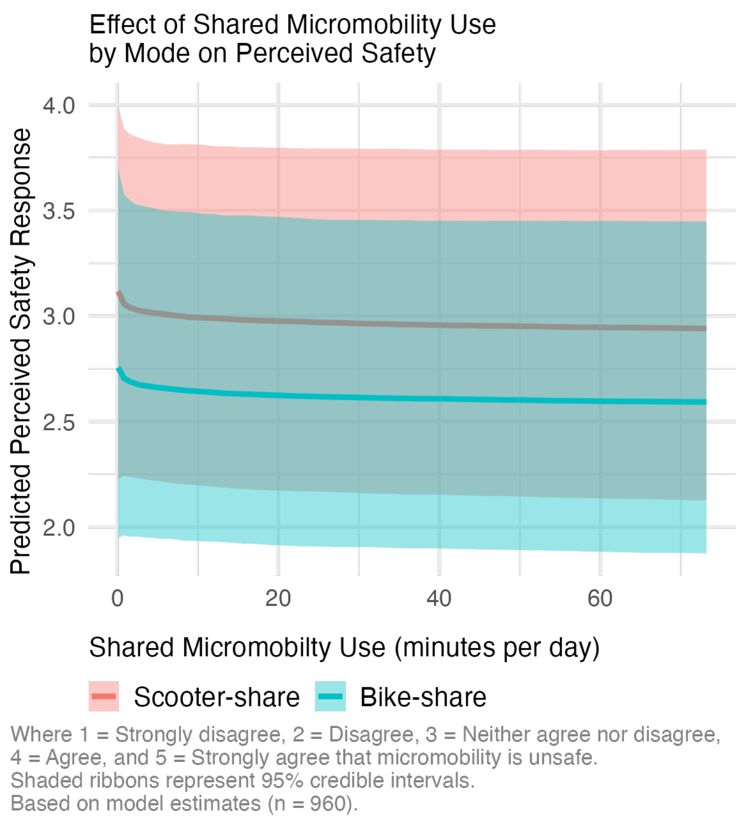

Figure 4.10
Conditional effects of shared micromobility use by mode on perceived safety.

The model does predict that having a minimum of six months of prior experience to shared micromobility mode will improve the user's perceived safety of shared micromobility

(Figure 4.11). Further experience beyond a year could continue to improve this perception, but with the amount of uncertainty in the prediction and the slight change in the mean suggests that only the first six months of experience would have any measurable effect. Another observation is responses on average for scooter share are neutral after a minimum of six months of experience, but less than six months trends towards perceiving shared micromobility to be unsafe. On the other hand, bike share is generally neutral under six months and considered safer with more experience.

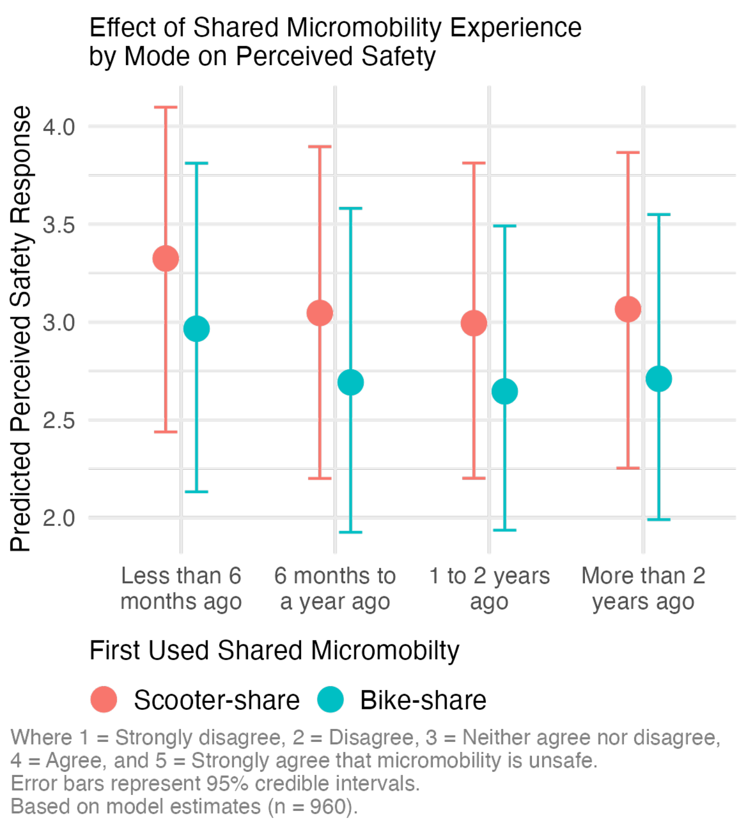

Figure 4.11
Conditional effects of shared micromobility experience by mode perceived safety.

According to the conditional effects *income*, there is a trend that would suggest that income may help predict what the predicted perceived safety response would be for a respondent (Figure 4.12). Users of shared micromobility in higher *income* groups (*$100 to $150k* and *More* *than $150k*) are predicted to perceive shared micromobility as safer than lower income groups, although the effect is still uncertain. This result for the effect of *income* shows that person-level characteristics are important in determining how safe a person will perceive shared micromobility.

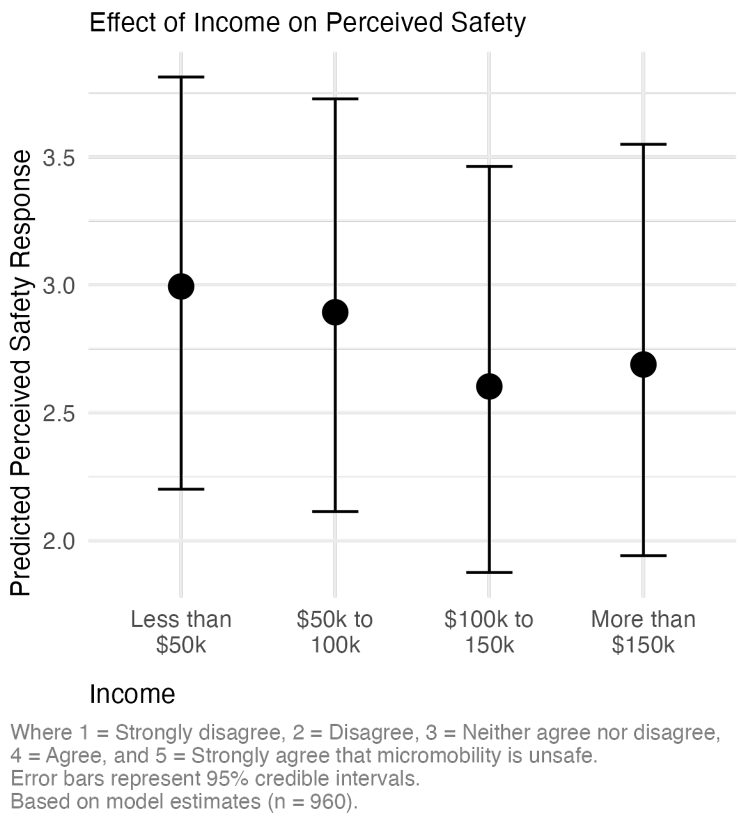

Figure 4.12
Conditional effects of income group on perceived safety.

We can be more certain that how often a person almost crashes shared micromobility is a good indicator of how safe they perceive shared micromobility to be, which was expected (Figure 4.13). There is more uncertainty with the higher frequencies of *almost crashing*, but there is a clear trend towards stronger feelings of safety as with lower frequencies of almost crashing, beginning with a mostly neutral average predicted response for *More than half of my trips* to much more disagreement that shared micromobility is unsafe.

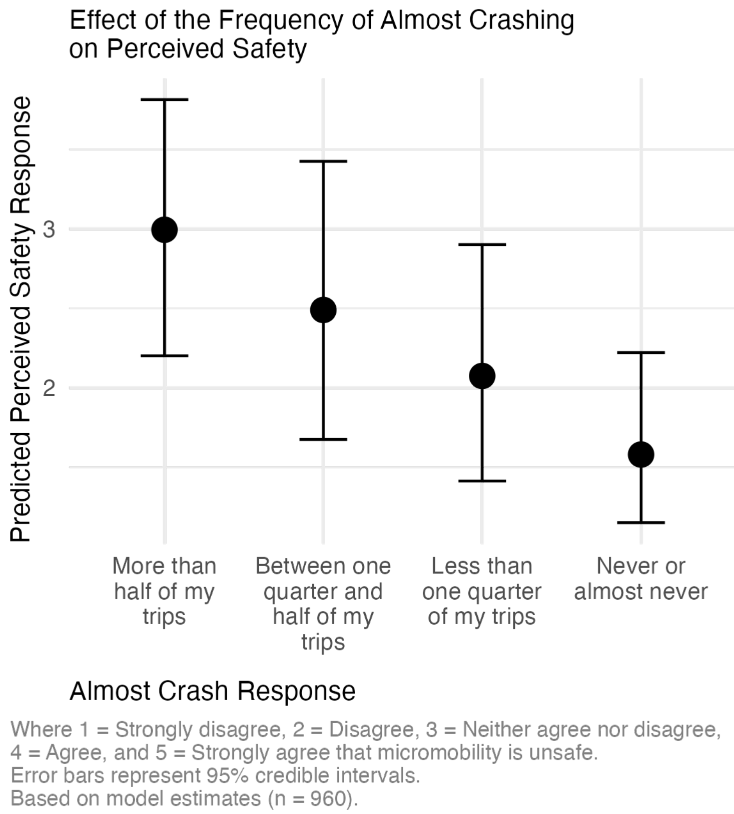

Figure 4.13
Conditional effects of the frequency of almost crashing shared micromobility on perceived safety.

In addition to user's perceived experiences with almost crashing influencing their perceived safety of shared micromobility, their response towards how important their concern for safety from traffic affects their travel choices also shows an expected trend for its influence on perceived safety (Figure 4.14). However, *concern for safety* shows more uncertainty than *almost crash* did for its expected effect on the response. Based on Figure 4.14, as a user of shared micromobility is more concerned about the safety of traffic, they are predicted to on average perceive shared micromobility as unsafe more than a user that is less likely to be making travel choices based on their concern for their safety from traffic. It is reasonable to expect that if a person is making travel decisions based on their safety, they have some concern for safety about traveling and therefore would be concerned about the safety of their travel mode, like shared micromobility.

Figure 4.14
Conditional effects of the importance of the concern for safety from traffic affecting travel choices on perceived safety.

Based on the posterior densities of the standard deviation parameters (Figure 4.15), we can be confident about the *City* (city-level identifier) not having significant variation between each city considering the posterior density is close to 0. The *Safety Dimension* (identifying if the response is about unsafe or worry crashing) being within a range close to 0 also suggests that the difference between *Unsafe* and *Worry Crashing* would not have a noticeable impact on the response. However, there is much more uncertainty with *Safety Dimension* than there is with *City* due to the wide distribution of the posterior density. The *Invitation Code* (person-level identifier) is much more certain and concentrated around 1.6. According to this result, we can expect more heterogeneity between each person, and we can conclude it is more important to the model who the respondent is rather than which city they are in or which specific safety topic they are responding to.

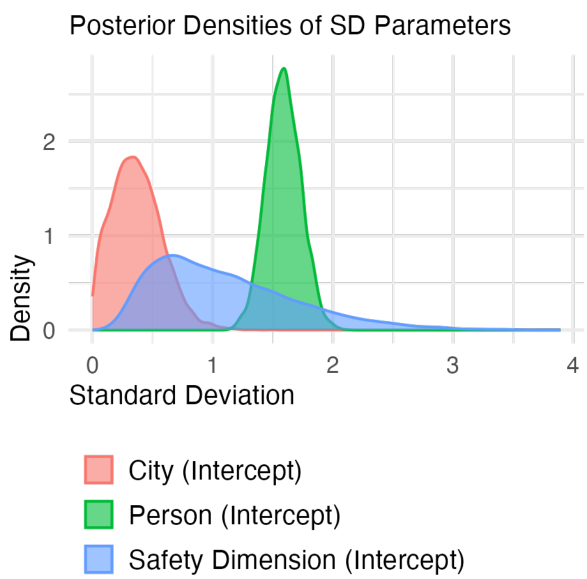

Figure 4.15
Posterior densities of the SD parameters.

According to the random effects of the changes in safety questions (Figure 4.16), there is a difference between the two dimensions in their sign – *Worry Crashing* is more positive and *Unsafe* is more negative. This shows that the response for *Worry Crashing* is more likely to bring the overall perceived safety response to the positive direction (towards perceiving shared micromobility to be unsafe) while *Unsafe* is more likely to bring it to the negative response direction (towards perceiving shared micromobility to be safer). The intervals for both *Worry Crashing* and *Unsafe* including 0 suggests that there is likely not a significant difference between the effect of the dimension being about worrying about crashing micromobility or feeling that the micromobility mode is unsafe.

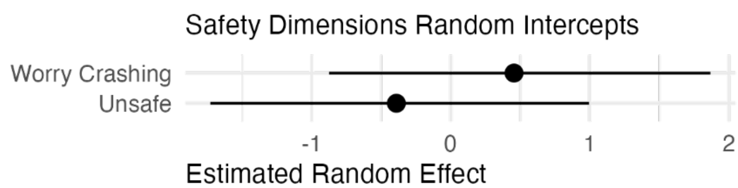

Figure 4.16
Estimated random effects by safety dimension.

From Figure 4.17, city intercepts are more uncertain for those with fewer respondents. As shown in Table 4.9, a large portion of the participants are in five major cities: Chicago, IL, New York, NY, Washington, D.C., San Francisco, CA, and Denver, CO, which show less uncertainty due to the higher populations of respondents. Interestingly, out of the five major cities in the data, New York, NY, is the only one to show a stronger trend towards perceiving shared micromobility is unsafe, compared to the other large cities which are mostly centered around 0 or negative (perceiving it as generally safe). This may signal that the city location is not as important to one's perceived safety of shared micromobility as a result of using shared micromobility except for the select few environments (like New York) considering most cities have similar estimated random effects.

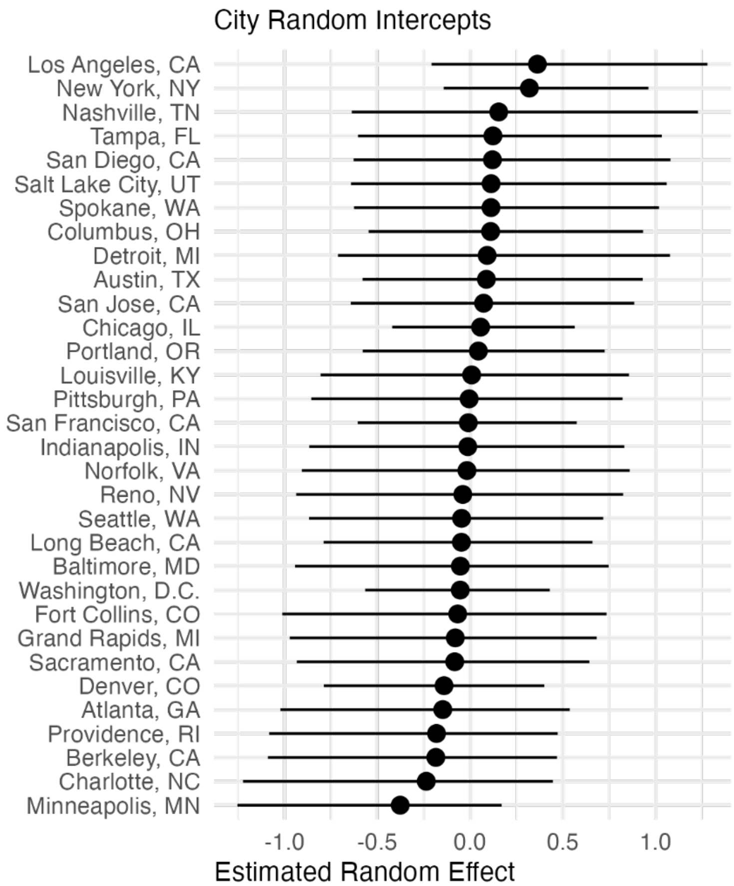

Figure 4.17
Estimated random effects by city.

Compared with cities, participants exhibit more between-person heterogeneity, and person-specific estimates are less precise (Figure 4.18). This result implies that the person-level variation in characteristics not directly described in the model are still important in determining how a person will perceive the safety of shared micromobility.

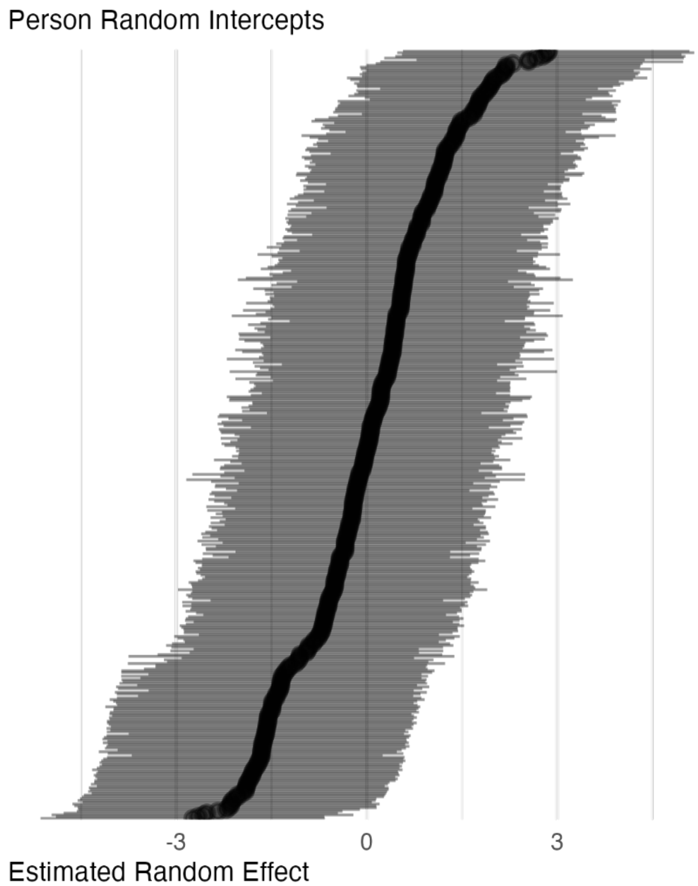

Figure 4.18
Estimated random effects by person.

Table 4.12 shows a summary of the results for the selected safety model H. From the results, *Bike share* as a mode is estimated to be 0.7 log-odds lower in the user's perceived safety with a 95% confidence interval less than 0 compared to the baseline of scooter share. Therefore, the model predicts it to be more likely that a person would perceive bike share as safer than scooter share considering that the more negative the response (the more disagreement) means the person feels the shared micromobility mode is safer. It is also worth noting that the only participant sociodemographic characteristic that shows any impact on perceived safety is *Income*; *Gender*, *Age*, and *Race* show uncertainty and no clear positive or negative impact. Additionally, *Dry Weather* may be more likely to improve perceptions of safety relative to

Humid and Windy Weather, but the effect is still uncertain. can improve perceptions of safety of riding shared micromobility.

Table 4.12
Summary statistics of the selected Safety model, Model H.

Parameter	Estimate	Est. Error	l-95% CI	u-95% CI
Intercept[1]	-3.4	0.9	-5.1	-1.7
Intercept[2]	-0.7	0.8	-2.4	0.9
Intercept[3]	0.6	0.8	-1.1	2.2
Intercept[4]	2.9	0.9	1.2	4.6
Bike share	-0.7	0.2	-1.1	-0.3
Exclusive	0.3	0.3	-0.2	0.9
log(Shared Micromobility Use (minutes per day))	-0.1	0.1	-0.2	0.1
Female	0.2	0.2	-0.3	0.6
Income $50k to $100k	-0.2	0.3	-0.8	0.4
Income $100k to $150k	-0.8	0.3	-1.4	-0.1
Income More than $150k	-0.6	0.3	-1.2	0.0
Age 35 to 55	0.1	0.2	-0.3	0.6
Age Over 55	0.1	0.4	-0.7	0.9
White	0.2	0.3	-0.3	0.7
First used 6 months to a year ago	0.1	0.4	-0.8	1.0
First used Less than 6 months ago	0.6	0.4	-0.1	1.4
First used More than 2 years ago	0.1	0.3	-0.4	0.7
Frequency Never	0.1	1.2	-2.4	2.5
Frequency Less than one trip a month	1.0	0.5	0.1	1.9
Frequency 1 to 3 trips a month	0.5	0.3	-0.2	1.2
Frequency 1 to 2 trips a week	0.2	0.3	-0.4	0.8
Frequency 3 to 4 trips a week	-0.2	0.3	-0.7	0.4
Humid and Not Windy Weather	-0.2	0.4	-0.9	0.5
Dry Weather	-0.6	0.3	-1.2	0.1
More Residential	0.3	0.3	-0.2	0.8
mo(Almost Crash Response)	-1.1	0.3	-1.6	-0.6
mo(Concern Safety Traffic)	0.3	0.1	0.0	0.6

4.5 Conclusions

From the results of this study, it appears that users of shared micromobility are predicted to, on average, perceive that bike share is safer than scooter share. Unexpectedly, the increase in daily use of shared micromobility is not predicted to improve these sentiments. However, the long-term use of shared micromobility is important if a user has more than six months experience. If operators and policymakers can overcome any initial apprehension about using the shared micromobility services, and users are able to experience the service for longer than six months, they may feel these services are safer to use than they did before the six months on average. With the level of uncertainty present in the model results, this effect is shown to be greatly influenced by the individual, and this experience of using bike share or scooter share over time may not have a consistent benefit.

Despite the random effects by person (Figure 4.18) suggesting that the person-level characteristics are more important to one's perceived safety of shared micromobility than other information about their experience, the only sociodemographic characteristic in the model found to be important was *income*. Instead, individual responses towards *concern for safety* and the perceived experience captured by the *frequency of almost crashing* proved to be stronger predictors for perceived safety. This is an interesting result of this model because it might suggest that while person-level characteristics are very important to understanding how shared micromobility users perceive the safety of these services, to better predict a person's perceived safety of shared micromobility may rely on other additional unique person characteristics, perceptions, and experiences that this study did not measure. Future work on this topic should endeavor to identify other individual characteristics and preferences that may better predict a user's perceived safety of these systems. Identifying these predictors may help policymakers and shared micromobility operators better understand who is using these services and how to increase their usage to achieve their safety and public health goals. Future work should also consider the possibility that perceptions of safety may influence the use of shared micromobility, which is a direction of causality opposite to the one presented in this study. Individuals who perceive shared micromobility to be unsafe may be those who rarely use it, and therefore those riders would be less likely to be represented by studies like AMP which primarily capture frequent users. For example, between surveyed users and non-users of shared e-scooters, users were more likely than non-users to describe themselves as willing to take risks, and non-users placed more importance on using helmets (Pourfalatoun et al., 2023). A perceived lack of safety was also found to be a common deterrent for bicycling (Swiers et al., 2017). Not being able to understand how infrequent users or non-users of shared micromobility presents a gap in knowledge in the relationship between perceived safety and the use of shared micromobility.

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4.7 Appendix

Table 4.13
Safety Model A summary statistics.

Parameter	Estimate	Est. Error	l-95% CI	u-95% CI
Intercept[1]	-2.8	0.7	-4.3	-1.5
Intercept[2]	-0.3	0.7	-1.8	1.0
Intercept[3]	0.9	0.7	-0.6	2.2
Intercept[4]	3.1	0.7	1.6	4.4
Bike share	-0.9	0.2	-1.2	-0.5

Table 4.14
Safety Model B summary statistics.

Parameter	Estimate	Est. Error	l-95% CI	u-95% CI
Intercept[1]	-2.8	0.8	-4.3	-1.4
Intercept[2]	-0.3	0.8	-1.8	1.1
Intercept[3]	0.9	0.8	-0.6	2.3
Intercept[4]	3.2	0.8	1.6	4.6
Bike share	-0.8	0.2	-1.2	-0.5
Exclusive	0.2	0.3	-0.3	0.7
log(Shared Micromobility Use (minutes per day))	-0.1	0.1	-0.3	0.0

Table 4.15
Safety Model C summary statistics.

Parameter	Estimate	Est. Error	l-95% CI	u-95% CI
Intercept[1]	-2.8	0.8	-4.5	-1.3
Intercept[2]	-0.3	0.8	-1.9	1.2
Intercept[3]	0.9	0.8	-0.7	2.5
Intercept[4]	3.2	0.8	1.5	4.7
Bike share	-0.8	0.2	-1.2	-0.4
Exclusive	0.3	0.3	-0.3	0.8
log(Shared Micromobility Use (minutes per day))	-0.1	0.1	-0.3	0.0
Female	0.2	0.2	-0.3	0.6
Income $50k to $100k	-0.3	0.3	-0.8	0.3
Income $100k to $150k	-0.7	0.3	-1.3	0.0
Income More than $150k	-0.5	0.3	-1.1	0.1
Age 35 to 55	0.2	0.2	-0.3	0.6
Age Over 55	0.0	0.4	-0.7	0.8
White	0.2	0.2	-0.2	0.7

Table 4.16
Safety Model D summary statistics.

Parameter	Estimate	Est. Error	l-95% CI	u-95% CI
Intercept[1]	-2.5	0.9	-4.3	-0.9
Intercept[2]	0.1	0.9	-1.6	1.7
Intercept[3]	1.3	0.9	-0.4	2.9
Intercept[4]	3.6	0.9	1.9	5.3
Bike share	-0.7	0.2	-1.1	-0.3
Exclusive	0.3	0.3	-0.2	0.9
log(Shared Micromobility Use (minutes per day))	-0.1	0.1	-0.3	0.1
Female	0.2	0.2	-0.3	0.7
Income \$50k to \$100k	-0.3	0.3	-0.9	0.3
Income \$100k to \$150k	-0.7	0.3	-1.3	0.0
Income More than \$150k	-0.5	0.3	-1.1	0.2
Age 35 to 55	0.2	0.2	-0.3	0.6
Age Over 55	0.1	0.4	-0.7	0.9
White	0.2	0.3	-0.3	0.7
First used 6 months to a year ago	0.1	0.4	-0.7	0.9
First used Less than 6 months ago	0.5	0.4	-0.3	1.3
First used More than 2 years ago	0.1	0.3	-0.4	0.6
Frequency Never	-0.1	1.3	-2.7	2.3
Frequency Less than one trip a month	0.8	0.5	-0.2	1.7
Frequency 1 to 3 trips a month	0.3	0.3	-0.4	1.0
Frequency 1 to 2 trips a week	0.0	0.3	-0.6	0.6
Frequency 3 to 4 trips a week	-0.3	0.3	-0.8	0.3

Table 4.17
Safety Model E summary statistics.

Parameter	Estimate	Est. Error	l-95% CI	u-95% CI
Intercept[1]	-3.5	0.8	-5.0	-1.9
Intercept[2]	-0.8	0.8	-2.4	0.7
Intercept[3]	0.4	0.8	-1.1	2.0
Intercept[4]	2.8	0.8	1.2	4.3
Bike share	-0.6	0.2	-1.0	-0.2
Exclusive	0.3	0.3	-0.3	0.9
log(Shared Micromobility Use (minutes per day))	-0.1	0.1	-0.2	0.1
Female	0.2	0.2	-0.3	0.7
Income $50k to $100k	-0.2	0.3	-0.8	0.3
Income $100k to $150k	-0.7	0.3	-1.3	0.0
Income More than $150k	-0.5	0.3	-1.1	0.1
Age 35 to 55	0.2	0.2	-0.3	0.6
Age Over 55	0.1	0.4	-0.7	0.9
White	0.2	0.2	-0.3	0.7
First used 6 months to a year ago	0.1	0.4	-0.7	0.9
First used Less than 6 months ago	0.6	0.4	-0.2	1.4
First used More than 2 years ago	0.1	0.3	-0.5	0.6
Frequency Never	0.2	1.2	-2.3	2.6
Frequency Less than one trip a month	1.0	0.5	0.1	1.9
Frequency 1 to 3 trips a month	0.4	0.3	-0.2	1.1
Frequency 1 to 2 trips a week	0.2	0.3	-0.4	0.8
Frequency 3 to 4 trips a week	-0.2	0.3	-0.7	0.4
mo(Almost Crash Response)	-1.0	0.2	-1.5	-0.5

Table 4.18
Safety Model F summary statistics.

Parameter	Estimate	Est. Error	l-95% CI	u-95% CI
Intercept[1]	-3.3	0.8	-4.9	-1.7
Intercept[2]	-0.6	0.8	-2.2	1.0
Intercept[3]	0.6	0.8	-1.0	2.2
Intercept[4]	3.0	0.8	1.4	4.6
Bike share	-0.6	0.2	-1.0	-0.2
Exclusive	0.3	0.3	-0.3	0.9
log(Shared Micromobility Use (minutes per day))	-0.1	0.1	-0.2	0.1
Female	0.2	0.2	-0.3	0.6
Income $50k to $100k	-0.2	0.3	-0.8	0.4
Income $100k to $150k	-0.7	0.3	-1.3	0.0
Income More than $150k	-0.5	0.3	-1.1	0.1
Age 35 to 55	0.1	0.2	-0.3	0.6
Age Over 55	0.1	0.4	-0.7	0.9
White	0.2	0.3	-0.3	0.7
First used 6 months to a year ago	0.0	0.4	-0.8	0.8
First used Less than 6 months ago	0.6	0.4	-0.2	1.4
First used More than 2 years ago	0.1	0.3	-0.4	0.6
Frequency Never	0.3	1.2	-2.2	2.6
Frequency Less than one trip a month	1.0	0.5	0.1	1.9
Frequency 1 to 3 trips a month	0.5	0.3	-0.2	1.2
Frequency 1 to 2 trips a week	0.2	0.3	-0.4	0.8
Frequency 3 to 4 trips a week	-0.2	0.3	-0.7	0.4
mo(Almost Crash Response)	-1.1	0.3	-1.6	-0.6
mo(Concern Safety Traffic)	0.2	0.1	0.0	0.6

Table 4.19
Safety Model G summary statistics.

Parameter	Estimate	Est. Error	l-95% CI	u-95% CI
Intercept[1]	-3.2	0.8	-4.8	-1.7
Intercept[2]	-0.6	0.8	-2.1	1.0
Intercept[3]	0.7	0.8	-0.9	2.2
Intercept[4]	3.1	0.8	1.5	4.7
Bike share	-0.6	0.2	-1.1	-0.2
Exclusive	0.3	0.3	-0.2	0.9
log(Shared Micromobility Use (minutes per day))	0.0	0.1	-0.2	0.1
Female	0.2	0.2	-0.3	0.6
Income $50k to $100k	-0.2	0.3	-0.8	0.4
Income $100k to $150k	-0.7	0.3	-1.4	0.0
Income More than $150k	-0.5	0.3	-1.2	0.1
Age 35 to 55	0.1	0.2	-0.4	0.6
Age Over 55	0.1	0.4	-0.7	0.9
White	0.2	0.3	-0.3	0.7
First used 6 months to a year ago	0.1	0.4	-0.8	0.9
First used Less than 6 months ago	0.6	0.4	-0.2	1.4
First used More than 2 years ago	0.1	0.3	-0.4	0.6
Frequency Never	0.0	1.2	-2.4	2.4
Frequency Less than one trip a month	1.0	0.5	0.1	2.0
Frequency 1 to 3 trips a month	0.5	0.3	-0.2	1.2
Frequency 1 to 2 trips a week	0.3	0.3	-0.3	0.9
Frequency 3 to 4 trips a week	-0.2	0.3	-0.7	0.4
Mean Weighted Average Absolute Grade	-0.1	0.1	-0.4	0.1
Mean Proportion Residential	0.0	0.1	-0.2	0.2
Mean Weighted Average Number of Lanes	0.2	0.1	-0.1	0.4
Mean Relative Humidity (2 m)	0.2	0.1	-0.1	0.4
Mean Precipitation	0.0	0.1	-0.3	0.2
Mean Wind Speed (10 m)	0.0	0.1	-0.3	0.2
mo(Almost Crash Response)	-1.1	0.3	-1.6	-0.6
mo(Concern Safety Traffic)	0.3	0.1	0.0	0.6

Table 4.20
Safety Model I summary statistics.

Parameter	Estimate	Est. Error	l-95% CI	u-95% CI
Intercept[1]	-4.3	1.7	-8.1	-1.2
Intercept[2]	-1.6	1.7	-5.4	1.5
Intercept[3]	-0.3	1.7	-4.1	2.8
Intercept[4]	2.1	1.7	-1.7	5.2
Bike share	-2.1	2.3	-7.4	1.9
Exclusive	0.1	0.4	-0.6	0.9
log(Shared Micromobility Use (minutes per day))	-0.2	0.2	-0.5	0.1
Female	0.2	0.2	-0.3	0.6
Income $50k to $100k	-0.3	0.3	-0.9	0.3
Income $100k to $150k	-0.8	0.3	-1.5	-0.1
Income More than $150k	-0.7	0.3	-1.3	0.0
Age 35 to 55	0.1	0.2	-0.4	0.6
Age Over 55	0.0	0.4	-0.8	0.9
White	0.2	0.3	-0.3	0.7
First used 6 months to a year ago	0.2	0.6	-1.0	1.4
First used Less than 6 months ago	0.7	0.5	-0.4	1.7
First used More than 2 years ago	0.0	0.4	-0.8	0.8
Frequency Never	0.5	1.3	-2.1	3.0
Frequency Less than one trip a month	1.4	0.7	0.1	2.7
Frequency 1 to 3 trips a month	1.2	0.5	0.2	2.3
Frequency 1 to 2 trips a week	0.6	0.5	-0.4	1.6
Frequency 3 to 4 trips a week	0.0	0.5	-1.0	1.0
Humid and Not Windy Weather	0.3	0.3	-0.4	1.0
Dry Weather	-0.3	0.6	-1.4	0.7
More Residential	-0.3	0.3	-0.8	0.2
Bike share:Exclusive	0.3	0.4	-0.5	1.1
Bike share:log(Shared Micromobility Use (minutes per day))	0.2	0.2	-0.2	0.6
Bike share:First used 6 months to a year ago	-0.2	0.8	-1.8	1.4
Bike share:First used Less than 6 months ago	-0.2	0.7	-1.7	1.2
Bike share:First used More than 2 years ago	0.1	0.5	-0.9	1.1
Bike share:Frequency Less than one trip a month	-0.6	0.9	-2.3	1.1
Bike share:Frequency 1 to 3 trips a month	-1.2	0.7	-2.6	0.2
Bike share:Frequency 1 to 2 trips a week	-0.4	0.6	-1.6	0.8
Bike share:Frequency 3 to 4 trips a week	-0.1	0.6	-1.3	1.1

Parameter	Estimate	Est. Error	l-95% CI	u-95% CI
mo(Almost Crash Response)	-1.6	0.6	-3.0	-0.6
mo(Concern Safety Traffic)	0.4	0.2	0.1	0.8
mo(Almost Crash Response):Bike share	0.6	0.7	-0.5	2.3
mo(Concern Safety Traffic):Bike share	-0.2	0.2	-0.6	0.2

5 Modeling Users' Perceived Effects of Shared Micromobility on Their Physical Activity

5.1 Introduction

Shared micromobility has emerged as a new pathway to increase physical activity through daily travel, complementing traditional active travel modes such as bicycling and walking. Shared micromobility systems have become more available to many across the United States as operators expand their services to new cities. As these systems become more available, the physical activity implications of their use become increasingly relevant in understanding how much activity people are getting in their day to day lives as people adopt these services into their routines. Likewise, as people use shared micromobility, it is possible they may begin to perceive changes in their physical activity that motivate their travel mode choices.

Some research has questioned the physical activity benefits of shared micromobility modes that have been electrified, especially e-scooters. Although shared micromobility services are often considered for reasons such as increasing accessibility or reducing car dependency, they may also offer the added benefit of supporting physical activity among residents. Even if the direct action of taking an e-scooter trip is not a significant benefit to one's health compared to sitting in a personal vehicle, it may lead to other increased physical activity that would make it preferable to driving for one's physical health. Additionally, while some researchers have found that e-bikers walk and bike less than those who bike on conventional bicycles (Castro et al., 2019), I suspect that there could be a difference in a user's perceived physical activity.

In this chapter I aim to determine whether if, in addition to the direct benefits of using active travel modes like shared micromobility described in the literature, users perceive they increased their physical activity as a result of shared micromobility use. This was possible using survey and travel diary data of micromobility users across various cities in the United States collected during Summer 2022 as part of the American Micromobility Panel (AMP) project (Fitch et al., 2023). In the survey included within the AMP project, participants were asked how their use of micromobility changed how much they walk, bike, and scoot. With these questions, I aimed to better understand how a person's shared micromobility use influences what they perceive to be changes in their physical activity via walking, biking, and scooting.

5.2 Literature Review

Active transportation modes are a proven way for people to increase their daily physical activity to more healthy levels as they replace their driving trips. Increasingly sedentary lifestyles have proven to be a growing global health concern (Tremblay et al., 2010), and the development of car-dependent urban environments is a contributor to this problem (Fishman et al., 2015). Active transportation has also been identified as an opportunity to counteract this trend with the recent popularity and expansion of shared micromobility services in cities across the world. Bicycling as a commute mode has been identified as an opportunity to increase physical activity (Donaire-Gonzalez et al., 2015). The widespread introduction of shared micromobility services to cities around the world has increased the accessibility of bicycling as a mode of transportation. While many of these systems include electric bicycles (e-bikes) and e-scooters, Castro et al. (2019) found that e-bikes were a benefit for physical activity of users when switching from driving, as was riding conventional bicycles. In addition, they found that switching from a bicycle to an e-bike did not generally reduce physical activity due to the trips made on e-bikes being longer in distance despite other research finding e-bikes being less physically intensive than conventional bicycles (Bernsten et al., 2017). There is growing evidence that riding e-scooters not only does not provide as much physical activity benefit as bicycles and e-bikes but could detract from a person’s potential daily physical activity as e-scooter trips replace potential walking and biking trips. Payne et al. (2025) found that riding an e-scooter in a laboratory environment resulted in less physical activity for the user than walking. This brings concerns that, with the increasing popularity of e-scooters as part of shared micromobility systems, that users may not be getting the increase in physical activity that proponents of shared micromobility and active transportation would hope for.

Existing research has also focused on shared micromobility, which may differ in physical activity benefits from traditional active travel modes. Bretones and Marquet (2023) observed users of shared micromobility (across bike share, e-bike share, and e-scooter share) having more physical activity daily than those who were not using micromobility. This result was more pronounced for bicycling modes compared to e-scooters, which the authors determined should not be considered an active travel mode (Bretones and Marquet, 2023). E-bike users have proven to increase their cycling (Sundfør and Fyhri, 2017), which allows them to offset any reduced physical activity observed due to the electric assist motor. Additionally, e-bikes are more appealing to potential users who are less physically active, and the result of their mode substitution does not reduce the level of physical activity (Sundfør and Fyhri, 2017).

While researchers have been considering that e-scooter use is not beneficial for physical activity compared to biking or walking, such as Sanders et al. (2022) determining that e-scooter trips were similar to driving trips in physical activity, it is worth noting that users of these modes may not perceive that to be the case. Grant-Muller et al. (2023) surveyed shared micromobility users and found that e-scooter riders were more likely to agree that riding an e-scooter required more physical activity to use than their usual mode of travel, and that their trip felt like exercise. Additionally, more users agreed than disagreed that they walked more because of these trips.

While these are not objective measures of physical activity of these users, this study supports my hypothesis that users may perceive that riding an e-scooter makes them a more active traveler, which could be instrumental in encouraging people to adopt more active modes of travel more regularly. There is some evidence that using bike share can introduce a person to a more physically active lifestyle (Auchincloss et al., 2022). Perceptions of cycling has an effect on the use of bike share systems; for example, if users found bicycling to be healthy, it positively influenced their use of the system (Fernández-Heredia et al., 2016).

Although shared micromobility requires some level of physical activity to use on its own, it is also worth considering that shared micromobility trips are not always additional trips occurring in isolation. Instead, shared micromobility trips may be changing a user's travel behavior and replacing trips they would have made using other modes. If a user of shared micromobility used to exclusively drive their vehicle for every trip they made, then the introduction of shared micromobility to their travel behavior has had a positive impact on their physical activity as driving is a sedentary activity. On the other hand, if a user of scooter share used to exclusively walk everywhere but now uses scooter share for a large proportion of their travel, they may experience a reduction in their physical activity.

According to the literature, the substitution of modes by bike share and scooter share may be similar. A literature review on bike share revealed that bike share trips have mostly been replacing walking trips and transit trips and may be having a VMT reduction effect (Fishman, 2016). A recent study in Shanghai, China, also found that bike share is most likely to replace walking and bus trips, and less likely to replace ride hailing and train trips (Gao et al., 2023). Vehicle substitution was not investigated, due to the lower rates of driving in Shanghai. Wang et al. (2023) reviewed the literature and found that e-scooters have a mode substitution effect; e-scooters may replace driving trips by a personal vehicle or taxi, but they also replace some other active travel by replacing walking trips. However, they found that e-scooter trips are much less likely to replace bicycling trips, meaning they are less in competition with other shared micromobility modes and instead compete with walking, or they are also induced trips. The potential for these shared micromobility services to reduce other active modes of travel suggests a need for a better understanding into how people are changing their physical activity as a result of using these services.

Therefore, research suggests a few pathways for changes in physical activity as a result of shared micromobility use. Users may substitute their vehicle trips, replacing a sedentary trip with a more active trip. Users may also make trips with bike share or scooter share that they would not have made otherwise, and these induced trips would contribute to more physical activity. On the other hand, walking trips are a potential opportunity for users to replace with bike share or scooter share trips. When walking trips are replaced, especially by scooter share trips, users are reducing their physical activity.

5.3 Methodology

5.3.1 Study Design

I studied the perceived changes in physical activity as a result of using shared micromobility using the resulting data from the AMP project (refer to Section 2.1 The American Micromobility Panel Project for details). I was able to connect micromobility users' responses to questions about their perceived changes in physical activity with their use of bike share and scooter share services during Summer 2022. With access to each user's trips, I calculated person-level aggregates of *shared micromobility use* in minutes per day for use as a predictor in the model to evaluate whether increased exposure to shared micromobility affects users' perceived changes in physical activity. I also incorporated characteristics of the built and natural environment as predictors because I expected they would affect a person's willingness to continue walking, biking, or scooting based on the quality of their surrounding built environment (such as the number of lanes or slope of the street) or the prevalence of good or deterring weather conditions (such as the amount of precipitation or wind). Prior research has shown that increases in rain can deter the amount of walking people do, while increases in temperature can encourage walking (Clark et al., 2014), so including them felt appropriate for this study of perceived changes in physical activity.

The response variable of the model is the result of the post-diary survey question asking users *How has your use of micromobility changed how much you walk, bike, and scoot?*, with an option to respond for each mode. These survey responses captured the three dimensions of perceived physical activity for my model: *biking*, *scooting*, and *walking*. For biking, scooting, and walking, respondents could answer *I do this much less*, *I do this slightly less*, *No change*, *I do this slightly more*, or *I do this much more*. Each participant in the study had the opportunity to answer for each mode once. To model these responses as a single response variable, I reshaped the data so that each mode-specific response is a separate row rather than a separate column. The new structure of the data maintains the dependency among responses provided by the same person. Reshaping the data was possible because the response categories for the three dimensions of physical activity all used the same Likert scale, and the Likert responses are preserved. I included other person-level characteristics, such as where they were recruited for the AMP study (*city*) and each person's sociodemographic characteristics (such as *income*). My conceptual model for how I expect a shared micromobility user's sociodemographic characteristics, city, *shared micromobility use*, experience with micromobility, their *desire for exercise* when making travel choices, and environment exposure influence their perceived changes in physical activity as a result of their shared micromobility use is shown below in Figure 5.1.

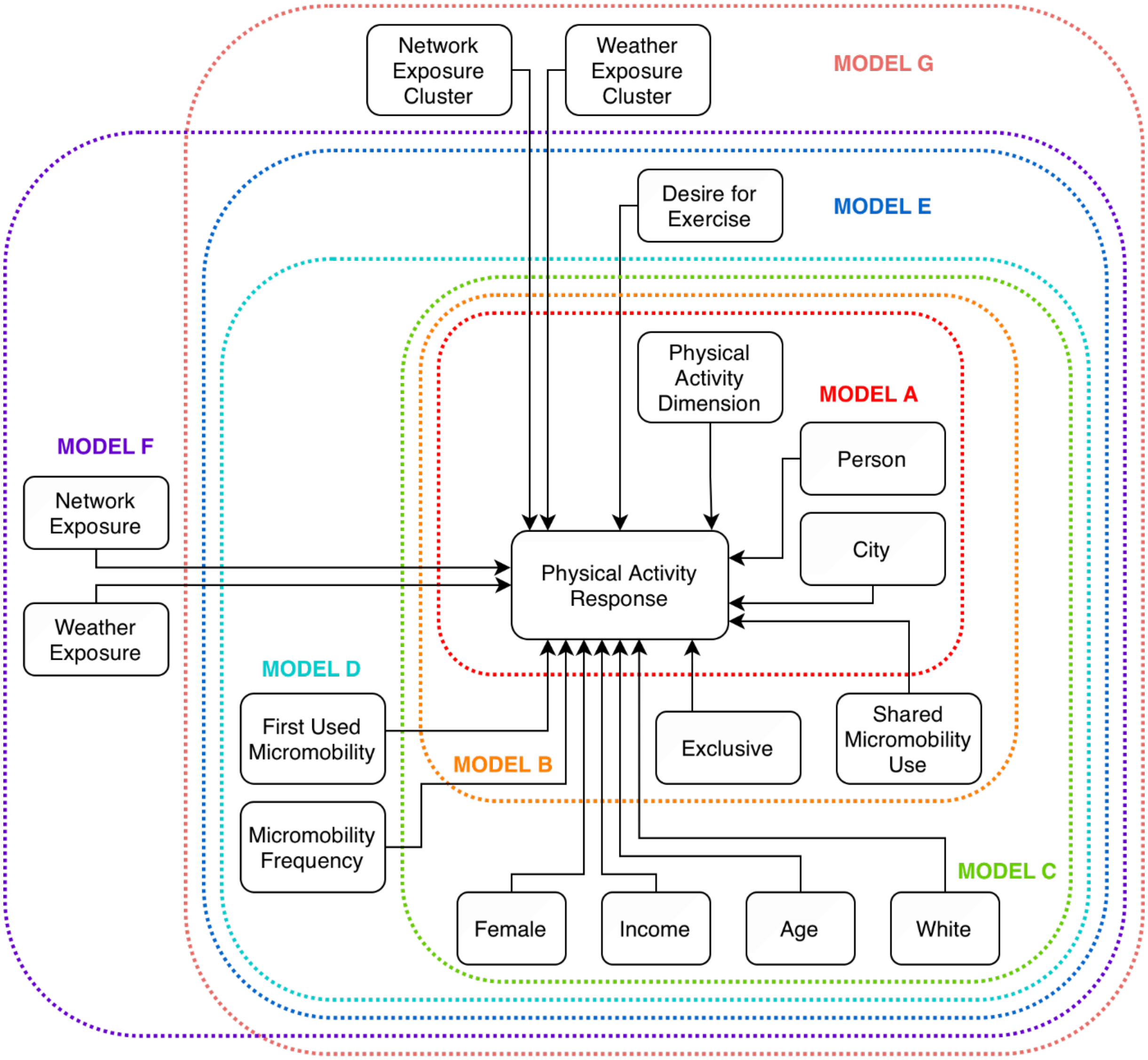

Figure 5.1
Diagram of the physical activity conceptual model.

5.3.2 Data Summaries

The results of the survey questions for the three physical activity related questions that are used to construct the physical activity response variable are shown in Figure 5.2. Most users said that because of their use of micromobility, they bike more than they did before. On the other hand, users were most likely to say they walked less because of their use of micromobility, and they were almost equally likely to not change or increase their scooting. Out of all three modes, users reduced their scooting the least compared to biking and walking. This suggests that scooting has the most potential to stick with participants as a physical activity, but walking is at the greatest risk of being replaced.

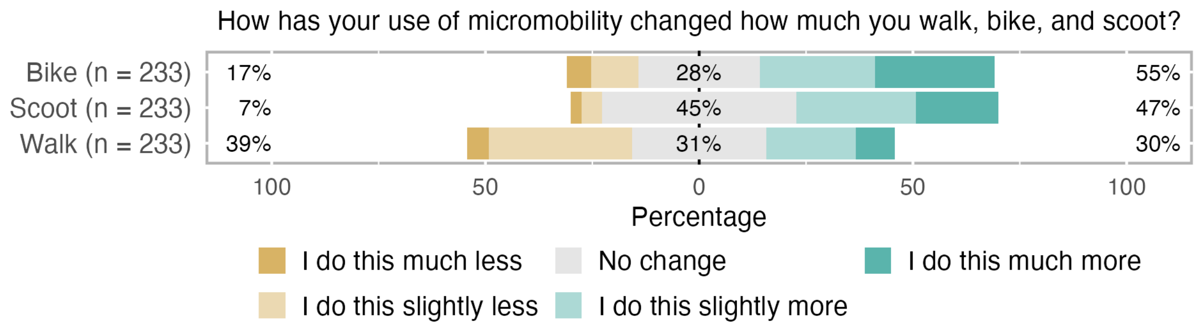

Figure 5.2
Participants' perceived changes in physical activity after using micromobility.

Table 5.1 shows the summary of the participants' characteristics. Each of these characteristics are a predictor, and each participant has a single set of values for these predictors. The participants are balanced among *income* categories, but they are much more skewed towards younger users of shared micromobility, and towards those who do not identify as *Female* and those who are *White*. Additionally, most participants only used one of the shared micromobility modes, and not both bike share and scooter share. Participants were more evenly distributed amongst *income* categories than they were for other characteristics.

Table 5.1
Summary of the participant characteristics used in the analysis.

Characteristic	Percentage (n = 233)
Exclusive Users	77.3
Female	34.8
White	76.0
Age Under 35	57.9
Age 35 to 55	36.5
Age Over 55	5.6
Income Less than $50k	20.6
Income $50k to 100k	29.2
Income $100k to 150k	20.2
Income More than $150k	30.0

Participants were also asked in the post-diary survey if they make their travel choices based on their desire for exercise. Most of the participants in this analysis find their desire for exercise to be moderately or very important to their travel choices, with only a small minority finding it to be not at all important (Table 5.2). This suggests that our participants are very active and attentive to their level of physical activity, which may lead to changes to their activity if they increase their use of shared micromobility.

Table 5.2
Summary of the participants' travel choices affected by their desire for exercise.

Importance	Percentage (n = 233)
Not at all important	3.9
Slightly important	17.6
Moderately important	32.6
Very important	29.6
Extremely important	16.3

Participants are generally more experienced with shared micromobility as a result of the recruitment process for the AMP study. Table 5.3 shows that participants are more likely to have more experience with bike share than scooter share, possibly because scooter share is a newer type of service compared to bike share. This may be related to the changes in mode use after using micromobility (Figure 5.2), where users were least likely to reduce their scooting. Users are more likely to be exclusive to one micromobility mode, and they are more experienced with bike share, suggesting that if they began using scooter share, they were more likely to stick with scooting as a mode and increase their usage rather than trying bike share.

Table 5.3
Summary of when each participant first used bike share and scooter share.

First Used	Bike share (n = 233)	Scooter share (n = 233)
Less than 6 months ago	8.6	11.2
6 months to a year ago	4.3	7.3
1 to 2 years ago	20.2	18.9
More than 2 years ago	67.0	62.7

Understandably, traveling by walking has higher frequencies of respondents considering that other modes require walking to find the shared micromobility device, or walking to transit or a vehicle (Table 5.4). Considering that the AMP participants were more experienced with bike share, it is also to be expected that they use it much more frequently than scooter share, with *5+ trips a week* being the most frequent response for bike share and *Less than one trip a month* being the most frequent response for scooter share. Frequency of use of micromobility services is seen as important to determining potential perceived changes in physical activity, as prior research has identified that higher frequency users were more likely to become more physically active out of a study of new bike share users (Auchincloss et al., 2022).

Table 5.4
Summary of how often each participant travels by each mode.

Frequency	Bike share (n = 233)	Scooter share (n = 233)	Walk (n = 233)
Never	3.0	9.4	0.0
Less than one trip a month	16.3	38.6	0.0
1-3 trips a month	13.7	17.2	3.0
1-2 trips a week	16.7	12.0	4.7
3-4 trips a week	17.2	9.4	13.7
5+ trips a week	33.0	13.3	78.5

Based on the data for trips made by micromobility, participants mostly experienced relatively humid micromobility trips on street segments with two to three lanes (Table 5.5). Windspeeds were not very high on average, and there was very little rain during the study period and across the various cities in the AMP project.

Table 5.5
Summary of each participants' exposure to the environment.

Variable	Mean	SD
Mean Weighted Absolute Average Grade	0.015	0.009
Mean Weighted Average Number of Lanes	2.543	0.578
Mean Proportion Residential	0.161	0.190
Mean Relative Humidity (2 m)	70.370	14.352
Mean Precipitation	0.115	0.294
Mean Windspeed (10 m)	12.090	5.717

Participants were not only more experienced with bike share and use bike share more frequently, but bike share use based on their trips tended to be longer than scooter share trips, with an average of 7.02 minutes compared to 2.45 minutes, respectively (Table 5.6).

Table 5.6
Summary of each participants' use of bike share and scooter share in minutes per day.

Mode	Mean	SD
Bike share	7.02	10.37
Scooter share	2.45	6.31

Additionally, despite there being many cities in the AMP study (Figure 2.1), most of the participants were recruited from a few large cities with established shared micromobility systems (Table 5.7). Within the data for the physical activity model, participants were recruited from 25 unique cities. Most participants being from a few large cities may explain the less than expected variation in weather and network exposure variables.

Table 5.7
Summary of which cities participants were recruited in.

City	Percentage of Participants (n = 233)
Atlanta, GA	0.9
Austin, TX	1.7
Baltimore, MD	0.4
Berkeley, CA	1.7
Charlotte, NC	0.4
Chicago, IL	17.6
Columbus, OH	2.1
Denver, CO	8.2
Fort Collins, CO	0.4
Grand Rapids, MI	0.4
Long Beach, CA	2.6
Los Angeles, CA	4.3
Minneapolis, MN	5.6
Norfolk, VA	0.4
New York, NY	10.7
Pittsburgh, PA	0.4
Portland, OR	4.3
Providence, RI	2.6
Sacramento, CA	2.1
Salt Lake City, UT	0.9
San Francisco, CA	9.4
San Jose, CA	2.6
Seattle, WA	0.4
Tampa, FL	0.4
Washington, D.C.	19.3

From Figure 5.3, there are no obvious patterns in the types of facilities participants used for their shared micromobility trips. They mostly traveled on segments with lower grades (not as steep), less residential segments (possibly more urban), and with a wider distribution of lanes between two and four lanes.

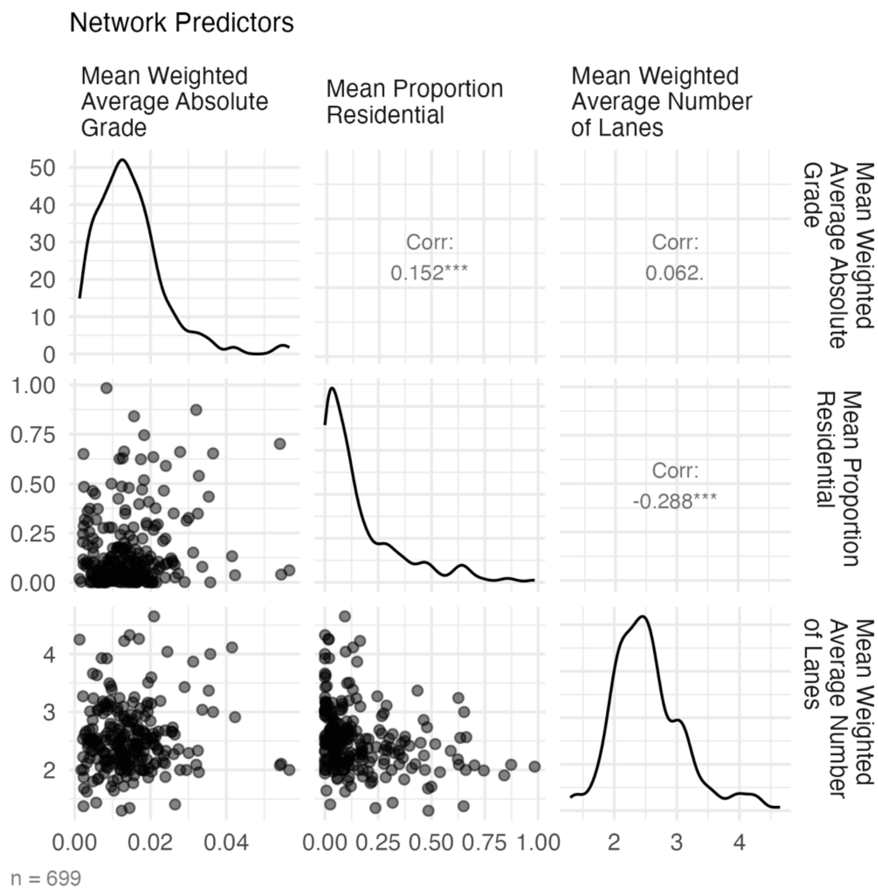

Figure 5.3
Distributions of the network predictors in the model.

Figure 5.4 demonstrates that precipitation events were rare during the shared micromobility trips by the participants in the model data, but that humidity and wind were less uniform across the data. It is possible that humidity and wind may vary across participants.

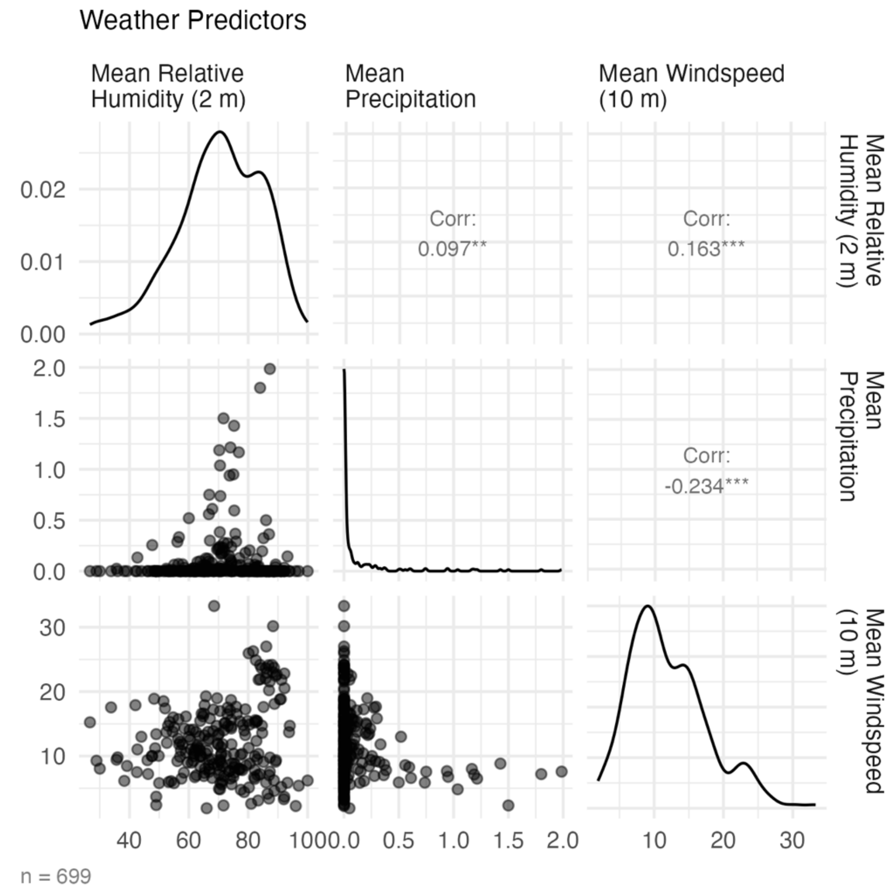

Figure 5.4
Distributions of the weather predictors in the model.

I expected the network predictors to have a similar impact on the response variable, as well as the three weather predictors. To capture their expected shared variation, I clustered individuals based on each group of predictors, creating a cluster representing the network predictors and another for the weather predictors. I expected that the categorizing individuals into these clusters would better describe their network or weather exposure throughout their shared micromobility trips and make it easier to describe the effects of these exposures on participants' changes in walking, biking, and scooting as a result of using micromobility.

The clustering method I selected was k-means clustering, and I evaluated the performance of the clustering based on the number of clusters using both the Elbow Method and the Silhouette Analysis. The Elbow Method calculates the total within-clusters sum of squares – the total of all squared distances between each cluster centroid and the observations within each cluster – across an increasing number of clusters beginning with 2. The total within-clusters sum of squares naturally declines as the number of clusters increases. When the total within-clusters sum of squares is plotted against the number of clusters, an "elbow" in the curve would identify the point where continuing to increase the number of clusters as diminishing returns on reducing the total within-clusters sum of squares. The Silhouette Analysis calculates an average "silhouette" value for an increasing number of clusters. An observation's silhouette considers the average distance between the observation and every other observation within its cluster as well as the average distance between the observation and observations in the neighboring cluster to define if the observation is classified well. Silhouettes are on a scale of -1 to 1, with larger values describing a better classification. When plotting the average silhouette width against the number of clusters, the ideal number of clusters would be at the highest point on the curve.

5.3.3 Clustering Based on the Network Variables

According to Figure 5.5, the Elbow Method does not present an obvious "elbow" (sharp change in the curve of plotted total within-cluster SS by number of clusters) that would suggest an ideal number of clusters for the weather exposure predictors. Based on the Silhouette Analysis, 2 clusters have a noticeably higher average silhouette width than having more clusters, which is suggesting that the ideal number of clusters based on the silhouette analysis is 2. When deciding on 2 clusters for the weather data, I considered that having a smaller number of clusters, especially given just three variables and a limited number of observations in the model data, would make interpreting their effects on the response variable simpler and more meaningful in the discussion.

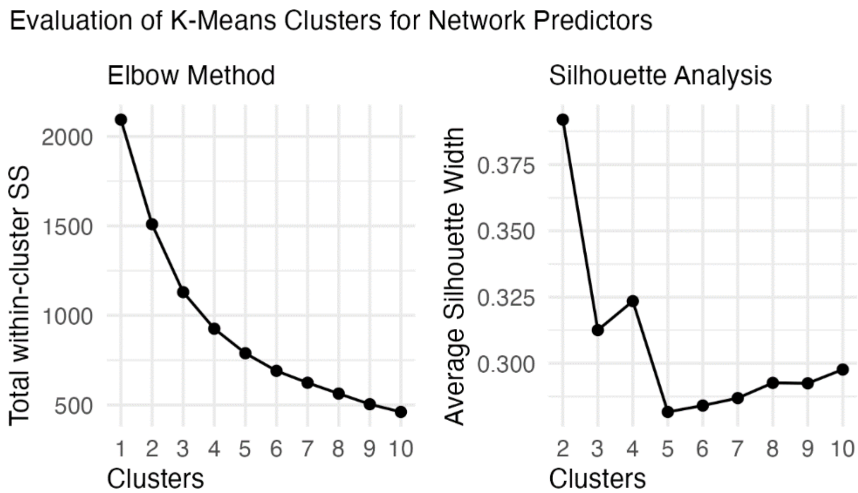

Figure 5.5
Evaluation of the number of k-means clusters for the clustering based on the network predictors.

The result of the k-means clustering for the network exposure predictors is shown in Figure 5.6. Plotting the data color-coded by the clusters, the clusters appear to be largely defined by the mean proportion of residential segments within an individual's trips. Cluster 1 contains the individuals whose trips are mostly not on residential streets, while Cluster 2 is defined by having higher proportions of residential streets. Cluster 1 and Cluster 2 do not differ much between the mean weighted average absolute grade, but steeper slopes appear in Cluster 2. Similarly, both clusters have individuals with a range of average number of lanes across their trips, but Cluster 1 may be more likely to have individuals with a higher number of lanes. Overall, the new network exposure cluster predictor is defined by a Cluster 1 which comprises individuals with trips that are less residential, flatter, and more likely to have a higher number of lanes on average, while Cluster 2 comprises individuals with trips that are much more residential, with more opportunity for steeper slopes and a lower number of lanes. Therefore, Cluster 1 is named *Less Residential* and Cluster 2 is named *More Residential*.

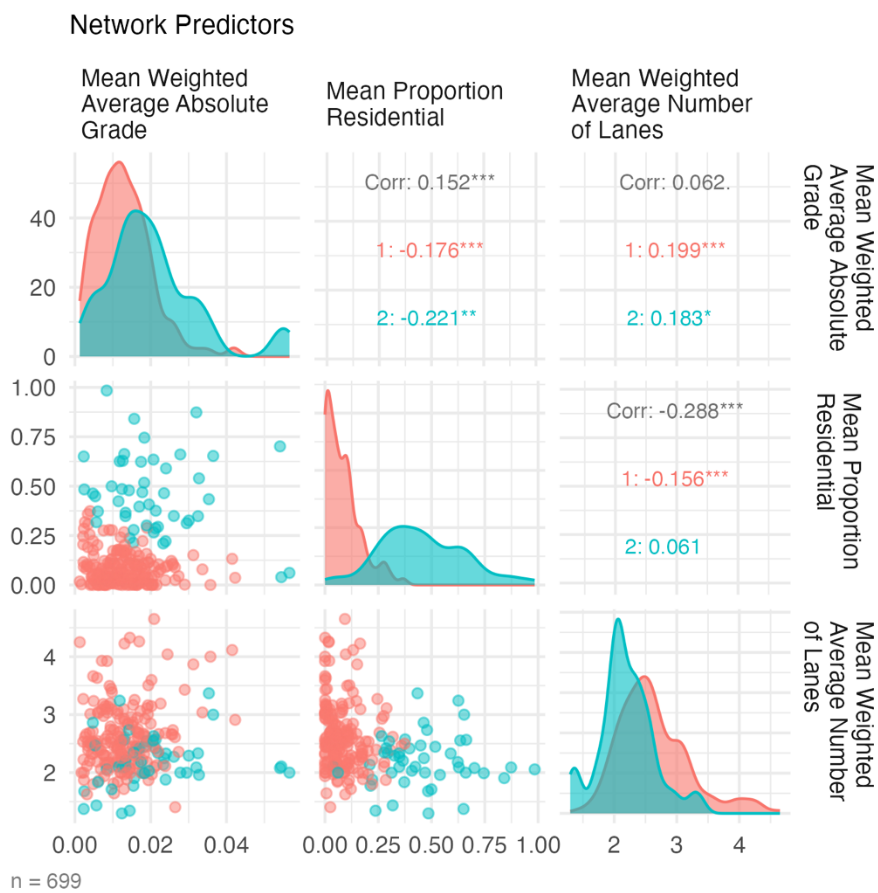

Figure 5.6
Results of clustering participants by the network exposure predictors.

5.3.4 Clustering Based on the Weather Variables

The clustering of the weather variables followed the same method as I described for the network variables. According to Figure 5.7, the Elbow Method for the weather variables also does not present an obvious “elbow” (sharp change in the curve of plotted total within-cluster SS by number of clusters) that would suggest an ideal number of clusters for the weather exposure predictors. Based on the Silhouette Analysis, 2 clusters have a noticeably higher average silhouette width than having more clusters, which is suggesting that the ideal number of clusters based on the silhouette analysis is 2. When deciding on 2 clusters for the weather data, I again preferred a fewer number of clusters to make interpreting their effects on the response variable simpler and more meaningful in the discussion.

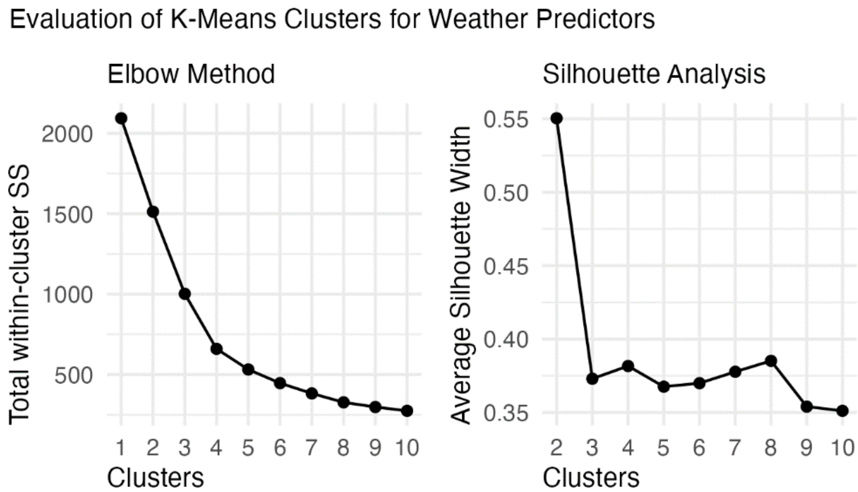

Figure 5.7
Evaluation of the number of k-means clusters for the clustering based on the weather predictors.

Figure 5.8 demonstrates the weather variable data color-coded by the 2 clusters determined by the k-means clustering algorithm. Cluster 2 appears to contain the individuals experienced rain and more humidity across their trips. Both clusters contain individuals with windy trips on average, but Cluster 1 appears to have individuals with lower *mean windspeeds* than Cluster 2, which has individuals with trips with more varied speeds. Based on these observations, we can generally consider Cluster 1 to be *Wetter Weather* and Cluster 2 to be *Drier Weather*. To put it simply, the clustering separated those individuals with trips with some noticeable weather events (higher wind speeds, precipitation, and humidity) from those with trips with generally fewer or no weather events.

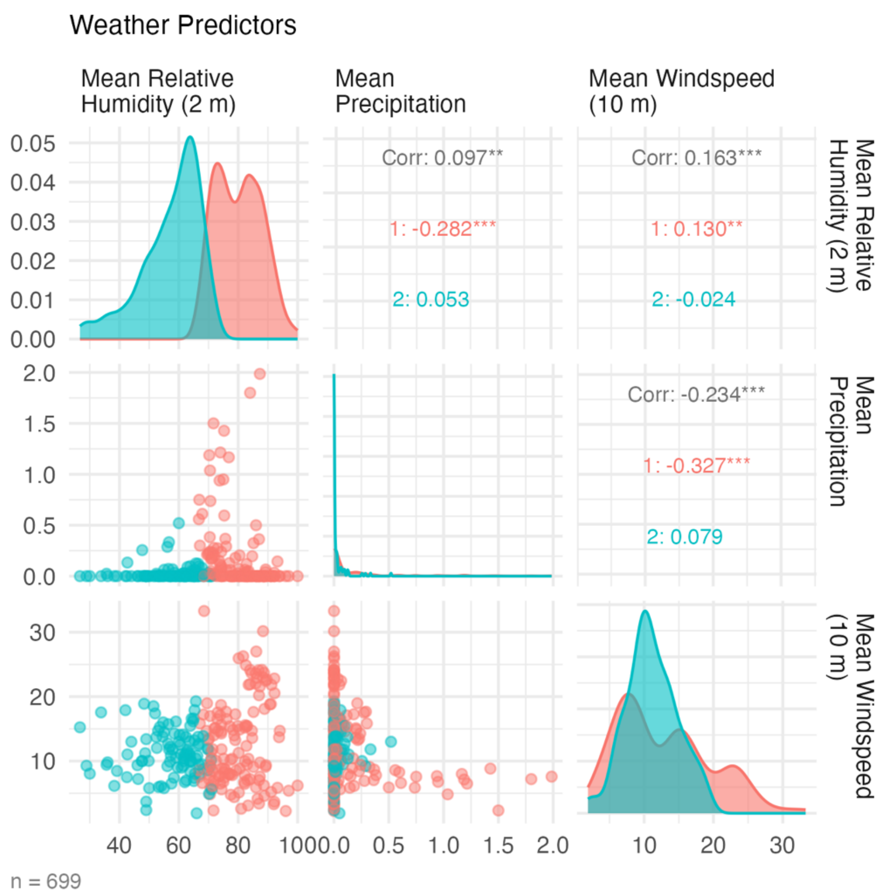

Figure 5.8
Results of clustering participants by the weather exposure predictors.

5.3.5 Model Descriptions

I created seven models to evaluate the impacts of the various predictors on the perceived changes in physical activity based on the general model described mathematically in Section 2.5 Statistical Modeling. I began with a simple model, and each subsequent model increases in complexity by introducing a new set of predictors, which are organized thematically by their expected contribution to the model. I approached the modeling with a simple model, increasing in complexity with each step to evaluate the contribution of each set of predictors while allowing the possibility that a simpler model might perform just as well. A summary of the seven models is shown in Table 5.8. Model A is the simplest model and contains what I considered to be the essential predictors of this analysis: the *physical activity question*, *person*, and *city*. *Person* and *city* identify the response at the person-level and city-level, respectively. The *physical activity question* identifies if the response is for perceived changes in walking, biking, or scooting. Model B builds upon Model A by introducing objective measures of shared micromobility use. This includes the *exclusive* predictor, which determines if they exclusively use a single shared micromobility mode or if they use both. This also includes *shared micromobility use* in minutes per day, which will allow for the model to predict how one's daily experience with shared micromobility may inform their perceived change in physical activity. Model C adds *sociodemographic* predictors to Model B, such as for whether they are female or not female, White or not White, which income category they belong to, and which age category they belong to. Model D builds upon Model C by adding *perceived shared micromobility experience* based on how long ago a participant thinks they first used the service and *perceived shared micromobility use* based on how often a participant thinks they use the service. Because the AMP project does not include any objective measures of a user's history with the shared micromobility services, these predictors serve as a proxy for familiarity with the services. Model E introduces the response to whether the participant makes *travel choices based on a desire for exercise*, which I expect would help the model in identifying a person's relationship with active travel and their tendency for physical activity. Model F adds *environmental exposure* with the previously described network predictors and weather predictors to Model E. Model G includes all the predictors as Model E, but instead of introducing all the environmental exposure predictors, it includes two predictors based on the clustering: one for the network exposure cluster and another for the weather exposure cluster.

Table 5.8
Descriptions of each physical activity model.

Model	Description
A	Physical Activity Dimension + Person + City
B	Model A + objective measures of shared micromobility use
C	Model B + sociodemographic predictors
D	Model C + perceived shared micromobility experience and use
E	Model D + travel choices based on a desire for exercise
F	Model E + environmental exposure predictors
G	Model E + network exposure cluster + weather exposure cluster

5.4 Results

The results presented in this section are based on Model G, the large model with the clustered network and weather exposures. While it is not the best performant of the seven models tested based on the LOO CV of each physical activity model (Table 5.9), I selected Model G to preserve as much information with the predictors due to the difference in performance between the simpler models B and A (which ranked best) not being drastic enough to justify dropping the additional predictors.

Table 5.9
Results of comparing the LOO CV of each physical activity model.

Model	ELPPM Difference	SE Difference
B	0.0	0.0
A	-0.8	2.6
C	-1.4	3.4
E	-7.7	6.0
D	-8.3	5.7
G	-9.2	6.1
F	-12.2	6.6

In Figure 5.9, the average rating of a shared micromobility user's perceived change in physical activity because of their used of shared micromobility is presented. Conditional effects plots (Figures 5.9 – 5.11) display the predicted probabilities for perceived changes in physical activity when all other covariates are held at their means and categorical predictors are held at their reference categories. The predictors *Bike share Use (minutes per day)* and *Scooter share Use (minutes per day)* were transformed by natural log because I expect there to be diminishing returns in the effect of using shared micromobility, and that a linear increase in the perceived change in physical activity would be unlikely. I present the results for perceived changes in physical activity as a latent variable scaled between 1 and 5, where the lower the values represent a reduction in perceived change in physical activity, and the higher values represent an increase. I chose to present the results this way instead of as discrete values because a user's perception of their change in physical activity in reality may occupy a spectrum between *I do this much less* and *I do this much more*, and I am more interested in the range of perceived change rather than the specific difference between categories of perceived change in physical activity.

Figure 5.9 shows a subtle difference between the effect of bike share and scooter share use in minutes per day on the predicted perceived physical activity response. Scooter share shows a positive trend with little diminishing returns with increased use of scooter share when looking at the mean within the interval, but the effects of both modes are quite uncertain. Bike share on the other hand, appears to be slightly negative and approaching no effect with increased use of bike share. The results show that on average, non-exclusive users of shared micromobility modes will perceive an increase in their physical activity (the mean is above 3.0). For exclusive users, it takes a few minutes of daily use of scooter share to become more positive on average, while for bike share, the model does not predict the average perceived change in physical activity to drop below the neutral response (less than 3.0) until more than 70 minutes of bike share use per day, which a person is unlikely to achieve.

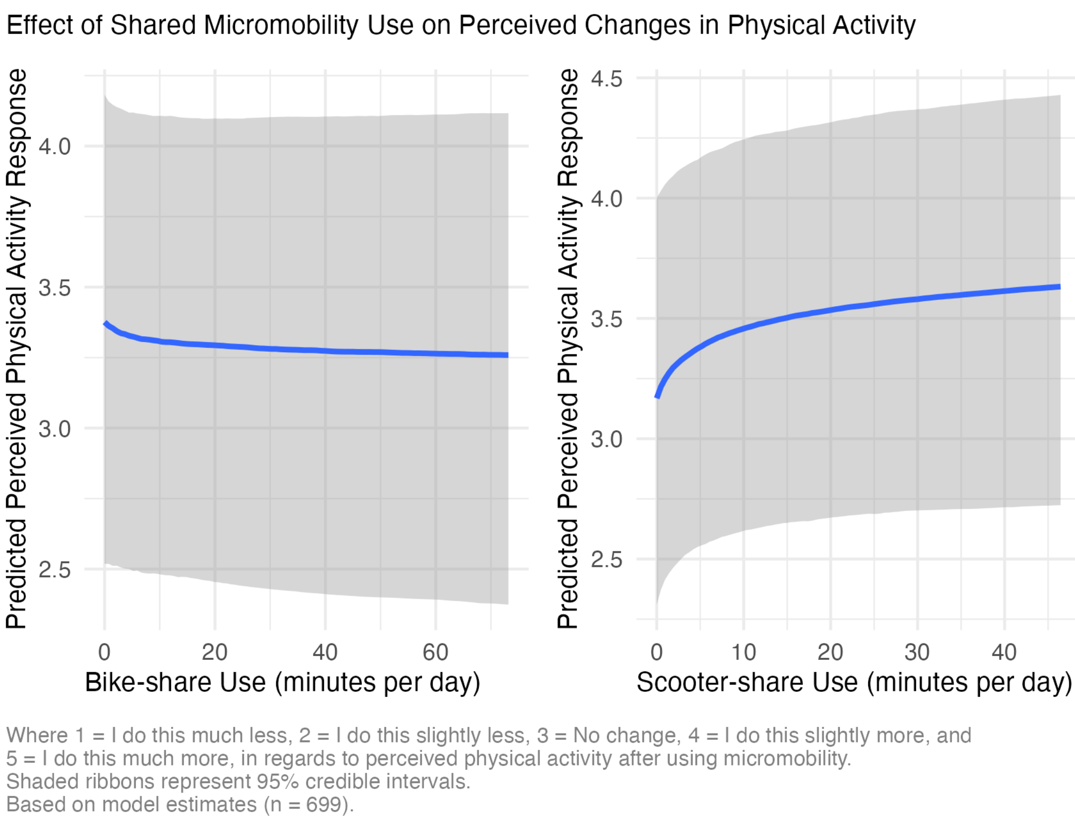

Figure 5.9
Conditional effects of shared micromobility use on perceived changes in physical activity.

The model predicts that the respondent's prior experience with shared micromobility is not a strong signifier of how much they will perceive they change their physical activity after using micromobility (Figure 5.10). The predicted responses across all experience brackets and for exclusive and non-exclusive users are wide across both positive and negative perceived changes in physical activity. Despite this uncertainty, there is a small difference in the shape of the plots between bike share and scooter share. Within the first year of use, the model would predict a slight trend of more positive perceived change in physical activity for bike share, and flat or negative trend for scooter share. After the first year of experience, this trend reverses to being more slightly negative for bike share over time and slightly positive for scooter share over time.

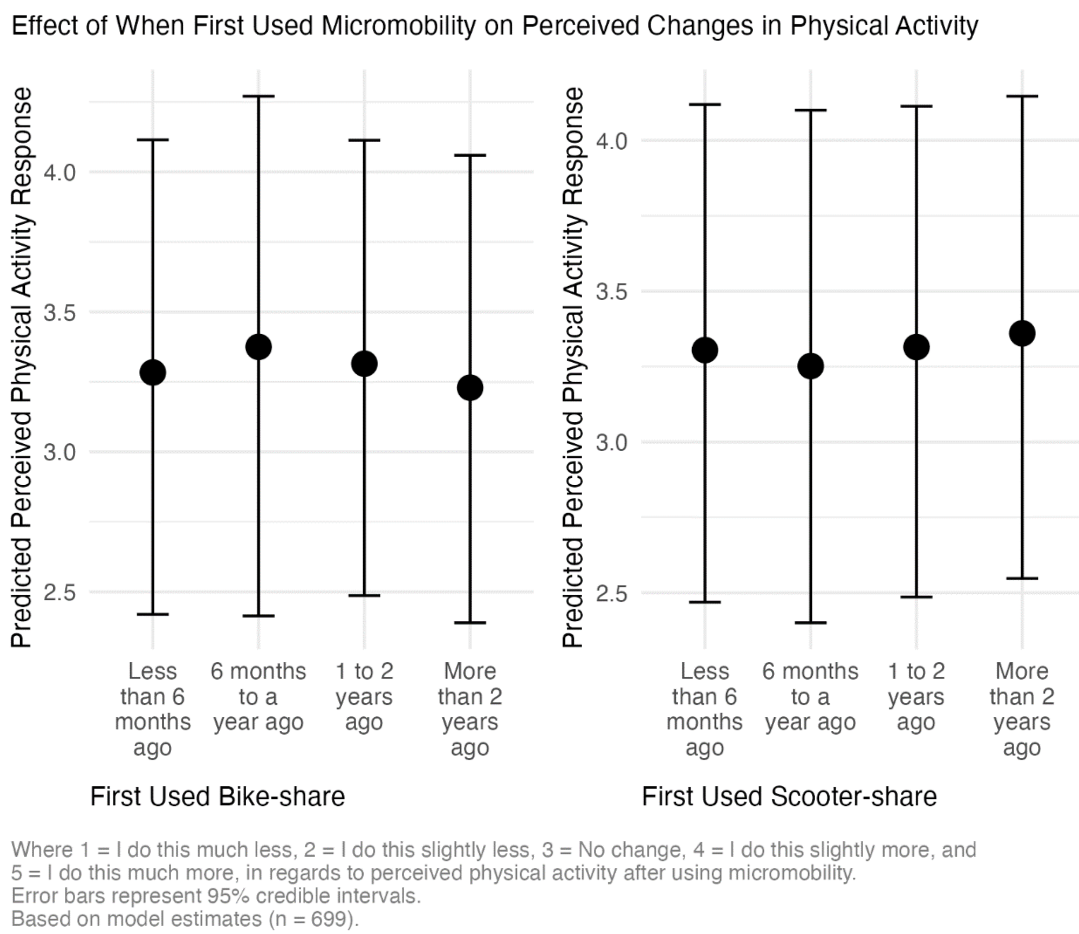

Figure 5.10
Conditional effects of when first used shared micromobility on perceived changes in physical activity.

According to the conditional effects of shared micromobility use by *age*, there is not a noticeable trend that would help predict what the predicted perceived safety response would be for a respondent (Figure 5.11). Respondents *over 55* years of age may trend towards more of an increase in physical activity, but there is a wider range of uncertainty compared to younger age brackets.

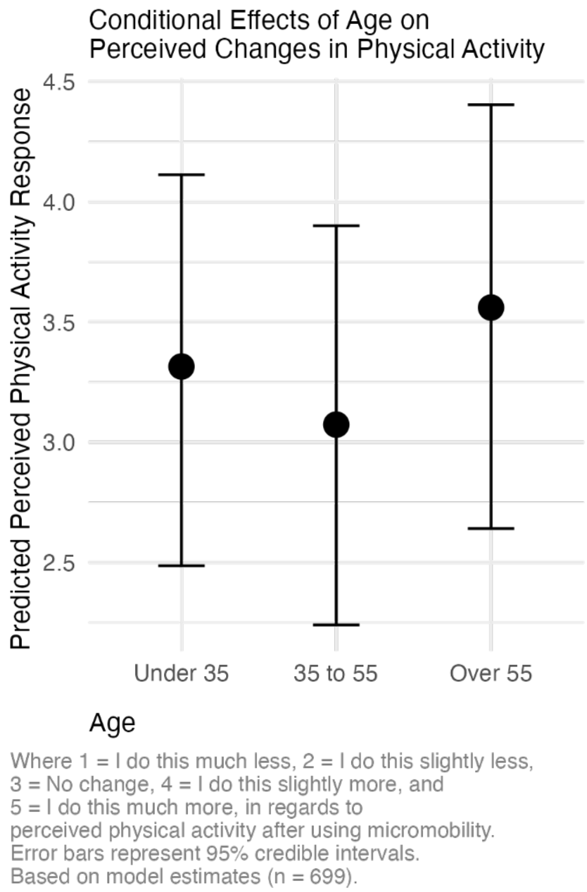

Figure 5.11
Conditional effects of shared micromobility use by age on perceived changes in physical activity.

Based on the posterior densities of the standard deviation parameters (Figure 5.12), we can be confident about *City* (city-level identifier) and *Person* (person-level identifier) being within a range close to 0 and above 0.5, respectively. *Physical Activity Dimension* (identifying the mode between walk, bike, or scoot) is much more uncertain despite peaking at around the same standard deviation as *Person*. According to this result, we can expect more of an effect from the person-level and mode identifiers than from the city-level identifier, with varying degrees of certainty.

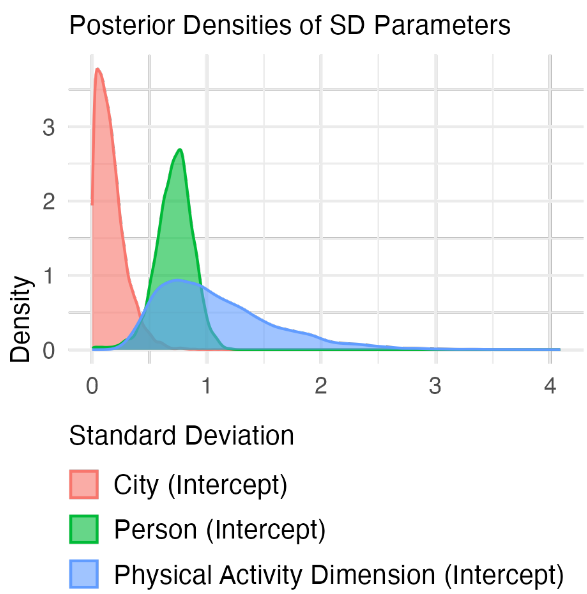

Figure 5.12
Posterior densities of the SD parameters.

According to the random effects of the changes in physical activity dimensions (Figure 5.13), there is not a significant difference in the magnitude of the uncertainty between the three modes. While bike and scoot show mostly positive range, walk is mostly negative. This shows that the response for walking is more likely to bring the overall change in physical activity response to the negative direction (towards reducing physical activity) which biking and scooting are more likely to bring it to the positive direction (towards increasing physical activity). This could be explained by some form of mode substitution, where walking may be more susceptible than biking and scooting to be reduced by shared micromobility use, and therefore respondents would be more likely to perceive that they walk less. All three physical activity dimensions straddle 0, suggesting the possibility that there may be no discernable effect between the physical activity dimension (the mode being discussed) and a user's perceived changes in physical activity.

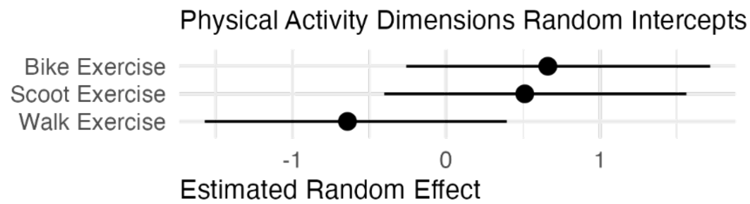

Figure 5.13
Estimated random effects by physical activity dimension.

City intercepts are uncertain (Figure 5.14), especially for cities like Salt Lake City, UT, Tampa, FL, Sacramento, CA, and Atlanta, GA. However, it should be noted that most of these cities with the large ranges of uncertainty are cities with much fewer participants. As shown in Table 5.7, a large portion of the participants are in five major cities: Chicago, IL, New York, NY, Washington, D.C., San Francisco, CA, and Denver, CO, which show less uncertainty due to the higher populations of respondents. Interestingly, out of the five major cities in the data, Denver, CO, is the only one to show a stronger trend towards perceiving their physical activity has reduced, compared to the other large cities which are mostly centered around 0. This may signal that the city location is not as important to one's perceived changes in physical activity as a result of using shared micromobility. The number of respondents in cities like Atlanta, GA, are few, so the negative trend for that city may be best explained by person-level variation rather than the city if most of the other city-level variations are unremarkable.

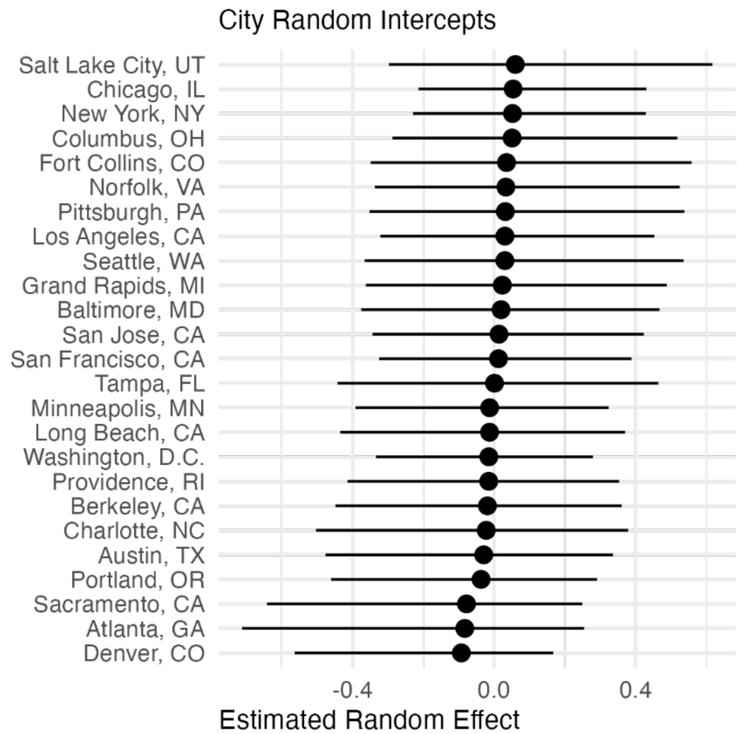

Figure 5.14
Estimated random effects by city.

The random effects by person (Figure 5.15) shows a broader spectrum of deviations across all the participants. This may suggest that the person-level variation is more meaningful to the model than the city-level, and there is less change in the perceived changes in physical activity between cities than between individuals.

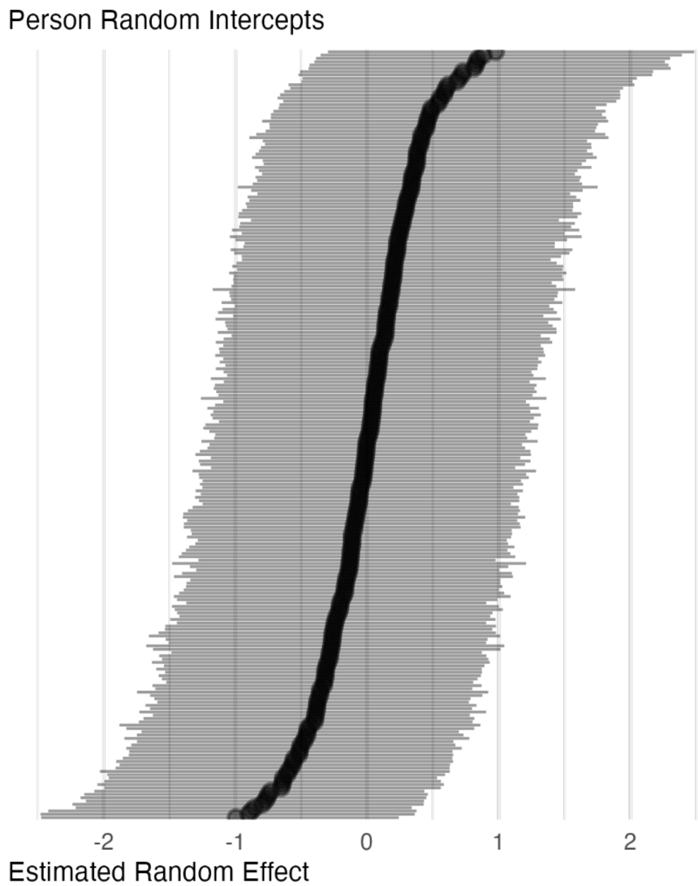

Figure 5.15
Estimated random effects by person.

Table 5.10 summarizes the model results. From the results, we can see that the model predicts it to be more likely that a respondent will perceive an increase in their change in physical activity as a result of using micromobility.

Table 5.10
Physical Activity Model G summary statistics.

Parameter	Estimate	Est. Error	l-95% CI	u-95% CI
Intercept[1]	-3.3	0.9	-5.0	-1.6
Intercept[2]	-1.4	0.9	-3.0	0.4
Intercept[3]	0.6	0.9	-1.1	2.4
Intercept[4]	2.1	0.9	0.4	3.9
Exclusive	-0.5	0.3	-1.0	0.1
log(Bike share Use (minutes per day))	-0.1	0.1	-0.3	0.2
log(Scooter share Use (minutes per day))	0.2	0.2	-0.1	0.5
Female	-0.2	0.2	-0.6	0.2
Income $50k to $100k	0.2	0.3	-0.4	0.7
Income $100k to $150k	0.7	0.3	0.1	1.3
Income More than $150k	0.5	0.3	-0.1	1.1
Age 35 to 55	-0.5	0.2	-0.9	-0.1
Age Over 55	0.5	0.4	-0.4	1.3
White	-0.1	0.2	-0.5	0.3
First used bike share 6 months to a year ago	0.1	0.5	-0.9	1.1
First used bike share Less than 6 months ago	-0.1	0.4	-0.9	0.7
First used bike share More than 2 years ago	-0.2	0.2	-0.7	0.3
First used scooter share 6 months to a year ago	-0.1	0.4	-0.9	0.7
First used scooter share Less than 6 months ago	0.0	0.4	-0.8	0.7
First used scooter share More than 2 years ago	0.1	0.3	-0.4	0.6
Bike share frequency 1-3 trips a month	-0.1	0.3	-0.7	0.6
Bike share frequency 3-4 trips a week	0.1	0.3	-0.6	0.7
Bike share frequency 5+ trips a week	-0.1	0.3	-0.7	0.5
Bike share frequency Less than one trip a month	-0.4	0.3	-1.1	0.3
Bike share frequency Never	-0.3	0.7	-1.7	1.0
Scooter share frequency 1-3 trips a month	-0.1	0.3	-0.8	0.5
Scooter share frequency 3-4 trips a week	0.0	0.4	-0.8	0.9
Scooter share frequency 5+ trips a week	-0.3	0.4	-1.1	0.5
Scooter share frequency Less than one trip a month	-0.4	0.3	-1.1	0.3
Scooter share frequency Never	-0.5	0.4	-1.4	0.3
Walk frequency 1-3 trips a month	0.6	0.8	-0.9	2.2
Walk frequency 3-4 trips a week	-0.1	0.5	-1.1	0.9
Walk frequency 5+ trips a week	0.8	0.5	-0.1	1.7

Parameter	Estimate	Est. Error	l-95% CI	u-95% CI
Drier Weather	-0.3	0.2	-0.8	0.2
More Residential	-0.2	0.2	-0.5	0.2
mo(Concern Desire for Exercise)	0.2	0.1	0.0	0.3

5.5 Conclusions

Based on the results of the conditional effects of shared micromobility use in minutes per day by mode (Figure 5.9), there is a noticeable difference between the effect of introducing bike share use and scooter share use to one's perceived change in physical activity. While the estimates for both modes show a lot of uncertainty and not a lot of difference between exclusive and non-exclusive use of each mode, the initial introduction of scooter share use to a person's daily travel shows a positive benefit to increasing their perceived physical activity response. Bike share shows almost no change across all durations of daily bike share use, with a potential slight decline. Considering that e-scooter is often considered by researchers as not providing as much physical activity as bike share, it is interesting that e-scooter is the mode that is most likely to lead to a perceived increase in biking, walking, or scooting. Because the response is the perceived change in physical activity, this result does not imply that bike share use reduces or does not change their actual physical activity, but it instead appears to not matter how much bike share is used per day in one's perceived amount of physical activity. This may describe people who already were traveling by some active mode and replacing some of these active trips with bike share, while scooter share trips were more likely being introduced to those who were more open to changes in their physical activity. Additionally, a user's experience with shared micromobility modes does not appear to have any recognizable trend with their perceived changes in physical activity (Figure 5.10), which means that promotions of shared micromobility for any physical activity benefits can target the general population, rather than just new or experienced users. Although, the population over 55 years old may perceive the most increase in their physical activity (Figure 5.11). While scooter share is not very physically demanding as a mode on its own, it may play a role in improving public health by encouraging its users to embrace more physical activity in their routines than they would have otherwise.

5.6 Discussion

As discussed earlier, I identified three likely pathways for increased physical activity as a result of shared micromobility use that would not rely on these expectations of experience with shared micromobility or personal characteristics to induce more travel. First, I expected based on the literature that the effect of substituting vehicle trips with shared micromobility trips would contribute to an increase in physical activity for the user. In Figure 5.16, I plot the physical activity response against the percentage of users' shared micromobility trips that they reported would otherwise have been made with a vehicle. Surprisingly, there is no clear trend between users' perceived changes in physical activity and the rate to which they substituted vehicle trips with shared micromobility. This challenges the assumption based on the literature that shared micromobility will provide some health benefit through replacing their vehicle trips. This lack of a trend was why vehicle substitution was not included in the model.

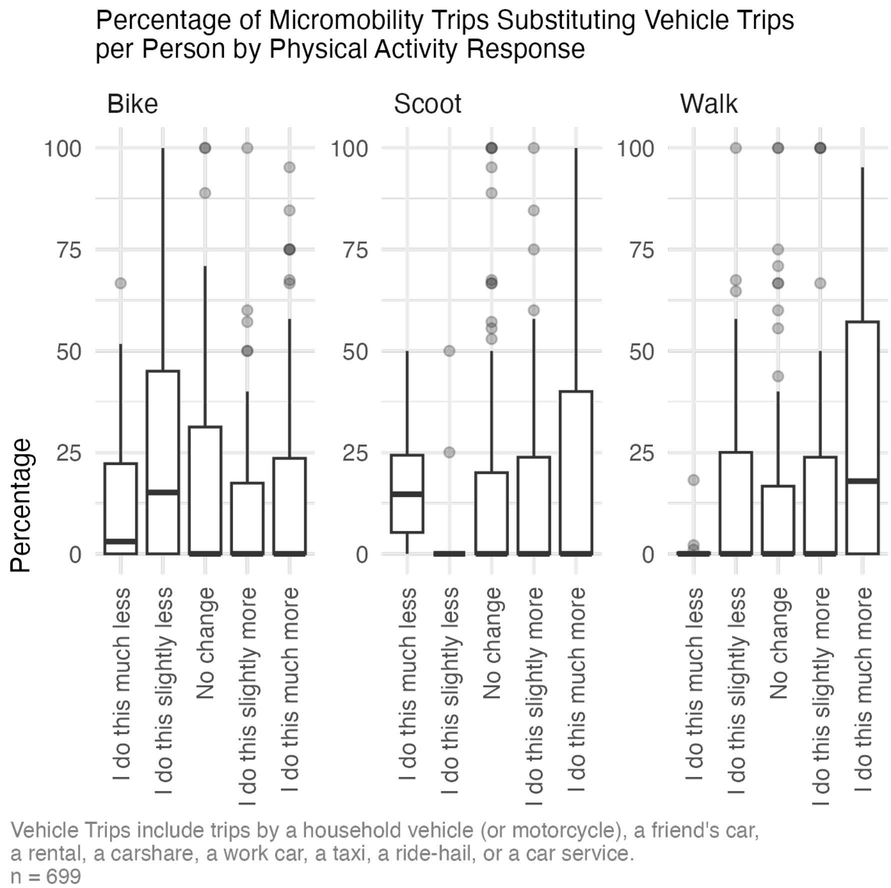

Figure 5.16
Percentage of micromobility trips substituting vehicle trips per person by physical activity response.

I also identified in the literature a possible negative effect of shared micromobility on one's physical activity by which users would replace their walking trips with trips by e-scooter, which have been found to be less physically demanding to operate compared to other active travel modes. However, just like with vehicle substitution, there was no obvious trend in the data between substituting walking trips and changes in a user's perceived physical activity (Figure 5.17). For example, for users replacing their walking trips with shared micromobility trips, they do not appear to report reliably walking less as a result of their shared micromobility use. Therefore, I also did not include walk substitution in the model despite its prevalence in the research.

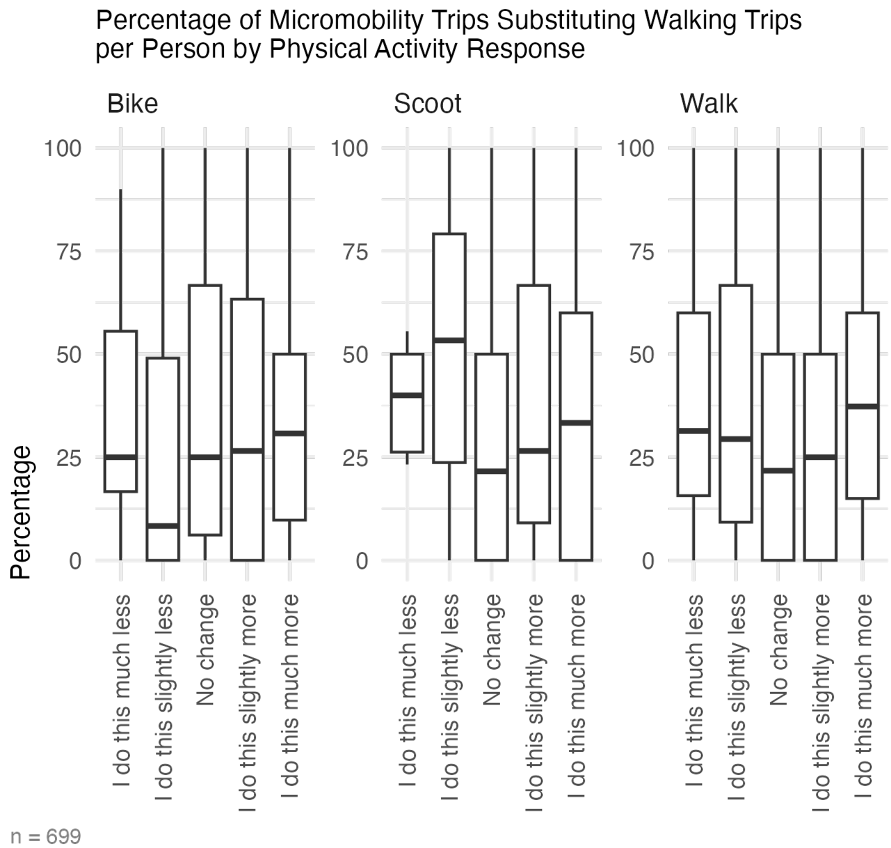

Figure 5.17
Percentage of micromobility trips substituting walking trips per person by physical activity response.

Finally, I considered that access to shared micromobility would induce trips on bike share or scooter share that the user would not have made otherwise on any other mode. This new access would potentially increase their physical activity with these new trips, regardless of the modes they used for their typical trips. Figure 5.18 also shows no meaningful relationship in our data between the percentage of users' shared micromobility trips that were induced and their perceived changes in physical activity and was not included in the model.

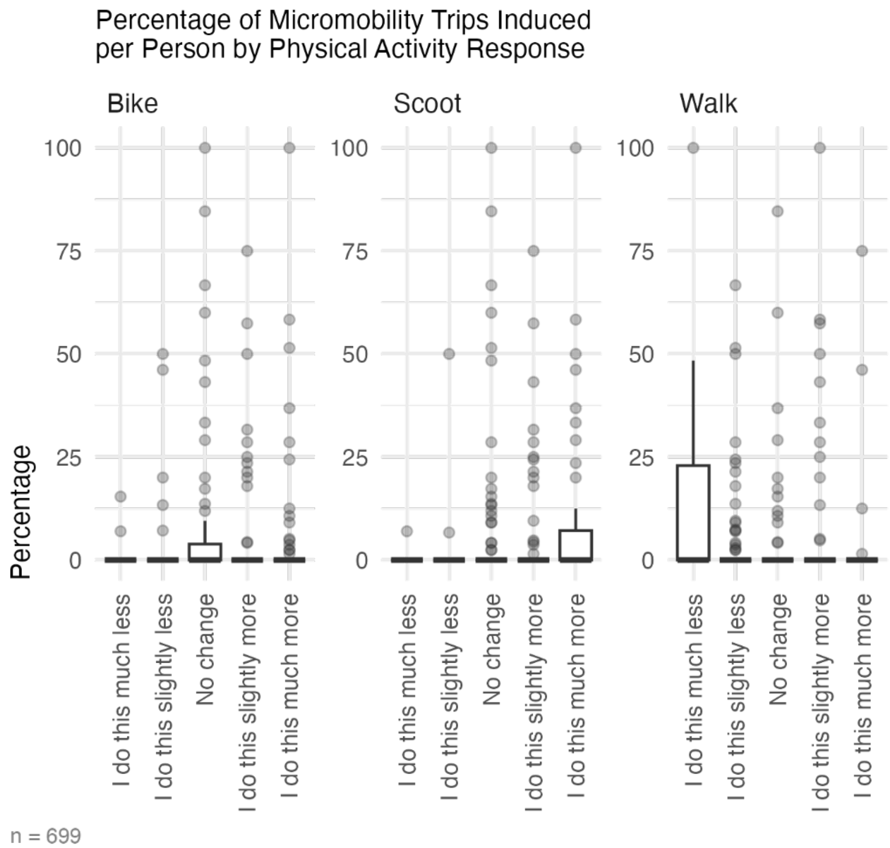

Figure 5.18
Percentage of micromobility trips induced per person by physical activity response.

Based on the data in the AMP project, there does not appear to be evidence to support these three pathways for a user perceiving they have increased their physical activity as a result of shared micromobility use. Additionally, their use and experience with the shared micromobility devices also do not have reliable effects on increasing this perceived change in physical activity. It is possible that these inconclusive results are due to the measurement of these values in the AMP survey. Respondents may have interpreted their *changes in biking, walking, or scooting as a result of their micromobility use* differently from one another or found the question too ambiguous. For example, respondents may not always equally estimate the amount of walking shared micromobility introduced to their routines as a result of walking to and from the devices, and not all respondents may have considered that walking as a change in their amount of walking. Future work should aim to improve this measurement of users' changes in perceived physical activity as a result of using shared micromobility to see if our inability to observe trends in these responses against mode substitution, induced micromobility trips, and experience with using shared micromobility still hold.

5.7 References

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5.8 Appendix

Table 5.11
Physical Activity Model A summary statistics.

Parameter	Estimate	Est. Error	l-95% CI	u-95% CI
Intercept[1]	-3.1	0.5	-4.1	-2.0
Intercept[2]	-1.2	0.5	-2.1	-0.2
Intercept[3]	0.6	0.5	-0.3	1.7
Intercept[4]	2.0	0.5	1.1	3.1

Table 5.12
Physical Activity Model B summary statistics.

Parameter	Estimate	Est. Error	l-95% CI	u-95% CI
Intercept[1]	-3.5	0.6	-4.6	-2.3
Intercept[2]	-1.6	0.6	-2.7	-0.4
Intercept[3]	0.2	0.6	-0.8	1.4
Intercept[4]	1.6	0.6	0.6	2.8
Exclusive	-0.5	0.2	-0.9	0.0
log(Bike share Use (minutes per day))	0.0	0.1	-0.2	0.1
log(Scooter share Use (minutes per day))	0.1	0.1	-0.1	0.3

Table 5.13
Physical Activity Model C summary statistics.

Parameter	Estimate	Est. Error	l-95% CI	u-95% CI
Intercept[1]	-3.4	0.6	-4.7	-2.1
Intercept[2]	-1.5	0.6	-2.7	-0.2
Intercept[3]	0.3	0.6	-0.8	1.6
Intercept[4]	1.8	0.6	0.6	3.1
Exclusive	-0.5	0.2	-0.9	0.0
log(Bike share Use (minutes per day))	0.0	0.1	-0.2	0.1
log(Scooter share Use (minutes per day))	0.2	0.1	-0.1	0.4
Female	-0.1	0.2	-0.5	0.3
Income $50k to $100k	0.1	0.2	-0.4	0.5
Income $100k to $150k	0.6	0.3	0.0	1.1
Income More than $150k	0.3	0.3	-0.2	0.8
Age 35 to 55	-0.4	0.2	-0.7	0.0
Age Over 55	0.6	0.4	-0.2	1.4
White	0.0	0.2	-0.4	0.4

Table 5.14
Physical Activity Model D summary statistics.

Parameter	Estimate	Est. Error	l-95% CI	u-95% CI
Intercept[1]	-3.2	0.9	-4.9	-1.5
Intercept[2]	-1.3	0.9	-3.0	0.4
Intercept[3]	0.6	0.9	-1.0	2.4
Intercept[4]	2.1	0.9	0.5	3.9
Exclusive	-0.4	0.3	-0.9	0.1
log(Bike share Use (minutes per day))	-0.1	0.1	-0.3	0.2
log(Scooter share Use (minutes per day))	0.3	0.2	-0.1	0.6
Female	-0.2	0.2	-0.6	0.2
Income $50k to $100k	0.1	0.3	-0.4	0.7
Income $100k to $150k	0.7	0.3	0.1	1.3
Income More than $150k	0.3	0.3	-0.3	0.9
Age 35 to 55	-0.4	0.2	-0.8	0.0
Age Over 55	0.6	0.4	-0.2	1.4
White	0.0	0.2	-0.5	0.4
First used bike share 6 months to a year ago	0.2	0.5	-0.8	1.2
First used bike share Less than 6 months ago	-0.1	0.4	-0.9	0.7
First used bike share More than 2 years ago	-0.1	0.2	-0.6	0.4
First used scooter share 6 months to a year ago	-0.1	0.4	-0.9	0.7
First used scooter share Less than 6 months ago	0.0	0.4	-0.7	0.8
First used scooter share More than 2 years ago	0.2	0.3	-0.3	0.7
Bike share frequency 1-3 trips a month	0.0	0.3	-0.7	0.6
Bike share frequency 3-4 trips a week	0.1	0.3	-0.5	0.7
Bike share frequency 5+ trips a week	-0.1	0.3	-0.7	0.6
Bike share frequency Less than one trip a month	-0.4	0.3	-1.1	0.2
Bike share frequency Never	-0.3	0.7	-1.6	1.1
Scooter share frequency 1-3 trips a month	-0.2	0.4	-0.8	0.6
Scooter share frequency 3-4 trips a week	-0.1	0.4	-0.9	0.7
Scooter share frequency 5+ trips a week	-0.4	0.4	-1.2	0.4
Scooter share frequency Less than one trip a month	-0.4	0.3	-1.1	0.2
Scooter share frequency Never	-0.5	0.4	-1.4	0.3
Walk frequency 1-3 trips a month	0.6	0.8	-0.8	2.1
Walk frequency 3-4 trips a week	-0.2	0.5	-1.2	0.8
Walk frequency 5+ trips a week	0.8	0.5	-0.1	1.7

Table 5.15
Physical Activity Model E summary statistics.

Parameter	Estimate	Est. Error	l-95% CI	u-95% CI
Intercept[1]	-3.2	0.9	-4.9	-1.5
Intercept[2]	-1.2	0.9	-2.9	0.5
Intercept[3]	0.7	0.9	-0.9	2.4
Intercept[4]	2.2	0.9	0.5	4.0
Exclusive	-0.4	0.3	-0.9	0.1
log(Bike share Use (minutes per day))	-0.1	0.1	-0.3	0.2
log(Scooter share Use (minutes per day))	0.2	0.2	-0.1	0.5
Female	-0.2	0.2	-0.6	0.2
Income $50k to $100k	0.2	0.3	-0.4	0.7
Income $100k to $150k	0.7	0.3	0.1	1.3
Income More than $150k	0.4	0.3	-0.2	1.0
Age 35 to 55	-0.5	0.2	-0.9	-0.1
Age Over 55	0.5	0.4	-0.3	1.3
White	-0.1	0.2	-0.5	0.3
First used bike share 6 months to a year ago	0.2	0.5	-0.8	1.2
First used bike share Less than 6 months ago	-0.1	0.4	-0.9	0.7
First used bike share More than 2 years ago	-0.1	0.2	-0.6	0.3
First used scooter share 6 months to a year ago	-0.1	0.4	-0.9	0.7
First used scooter share Less than 6 months ago	0.0	0.4	-0.8	0.7
First used scooter share More than 2 years ago	0.1	0.3	-0.4	0.6
Bike share frequency 1-3 trips a month	-0.1	0.3	-0.7	0.6
Bike share frequency 3-4 trips a week	0.1	0.3	-0.6	0.7
Bike share frequency 5+ trips a week	-0.1	0.3	-0.7	0.5
Bike share frequency Less than one trip a month	-0.4	0.3	-1.1	0.3
Bike share frequency Never	-0.3	0.7	-1.6	1.0
Scooter share frequency 1-3 trips a month	-0.1	0.3	-0.8	0.6
Scooter share frequency 3-4 trips a week	0.0	0.4	-0.8	0.8
Scooter share frequency 5+ trips a week	-0.3	0.4	-1.1	0.5
Scooter share frequency Less than one trip a month	-0.4	0.3	-1.1	0.2
Scooter share frequency Never	-0.6	0.4	-1.4	0.3
Walk frequency 1-3 trips a month	0.6	0.8	-1.0	2.1
Walk frequency 3-4 trips a week	-0.2	0.5	-1.2	0.8
Walk frequency 5+ trips a week	0.8	0.5	-0.1	1.7
mo(Concern Desire for Exercise)	0.2	0.1	0.0	0.3

Table 5.16
Physical Activity Model F summary statistics.

Parameter	Estimate	Est. Error	l-95% CI	u-95% CI
Intercept[1]	-3.2	0.9	-5.0	-1.5
Intercept[2]	-1.3	0.9	-3.0	0.5
Intercept[3]	0.7	0.9	-1.0	2.5
Intercept[4]	2.2	0.9	0.5	4.0
Exclusive	-0.4	0.3	-1.0	0.1
log(Bike share Use (minutes per day))	-0.1	0.1	-0.3	0.2
log(Scooter share Use (minutes per day))	0.3	0.2	0.0	0.6
Female	-0.2	0.2	-0.6	0.2
Income $50k to $100k	0.2	0.3	-0.4	0.7
Income $100k to $150k	0.7	0.3	0.1	1.4
Income More than $150k	0.5	0.3	-0.1	1.1
Age 35 to 55	-0.5	0.2	-0.9	-0.1
Age Over 55	0.5	0.4	-0.4	1.3
White	-0.1	0.2	-0.6	0.3
First used bike share 6 months to a year ago	0.1	0.5	-0.9	1.2
First used bike share Less than 6 months ago	-0.1	0.4	-0.9	0.8
First used bike share More than 2 years ago	-0.1	0.3	-0.7	0.4
First used scooter share 6 months to a year ago	-0.1	0.4	-0.9	0.7
First used scooter share Less than 6 months ago	-0.1	0.4	-0.9	0.7
First used scooter share More than 2 years ago	0.1	0.3	-0.4	0.7
Bike share frequency 1-3 trips a month	0.0	0.3	-0.7	0.7
Bike share frequency 3-4 trips a week	0.1	0.3	-0.6	0.7
Bike share frequency 5+ trips a week	-0.1	0.3	-0.7	0.6
Bike share frequency Less than one trip a month	-0.5	0.4	-1.2	0.2
Bike share frequency Never	-0.4	0.7	-1.9	1.0
Scooter share frequency 1-3 trips a month	-0.2	0.4	-0.9	0.5
Scooter share frequency 3-4 trips a week	0.0	0.4	-0.8	0.9
Scooter share frequency 5+ trips a week	-0.4	0.4	-1.2	0.4
Scooter share frequency Less than one trip a month	-0.5	0.4	-1.1	0.2
Scooter share frequency Never	-0.6	0.4	-1.5	0.3
Walk frequency 1-3 trips a month	0.6	0.8	-1.0	2.3
Walk frequency 3-4 trips a week	-0.2	0.5	-1.3	0.8
Walk frequency 5+ trips a week	0.8	0.5	-0.1	1.7

Parameter	Estimate	Est. Error	l-95% CI	u-95% CI
Mean Weighted Average Absolute Grade	0.0	0.1	-0.2	0.2
Mean Proportion Residential	-0.1	0.1	-0.3	0.1
Mean Weighted Average Number of Lanes	-0.1	0.1	-0.3	0.1
Mean Relative Humidity (2 m)	0.1	0.1	-0.1	0.3
Mean Precipitation	-0.2	0.1	-0.4	0.0
Mean Wind Speed (10 m)	-0.2	0.1	-0.4	0.1
mo(Concern Desire for Exercise)	0.2	0.1	0.0	0.3

6 Conclusions

I explored the impacts of riding shared micromobility on a person's perceived mental wellness, safety, and changes in physical activity. This research led to the development of models for the perceived wellness outcomes based on a user's characteristics, their use of shared micromobility, their exposure to the environment, and other relevant factors measured in the travel survey. Ultimately, the results of these models suggest that predicting the impact of shared micromobility use on one's perceived mental wellness, safety, and changes in physical activity may rely on factors not investigated in the AMP project, especially related to the differences in the individual. In addition, further thought as to how to improve the measurement of these outcomes is needed. For example, researchers should think about how to better measure perceived – or actual – changes in physical activity as a result of micromobility use that would hopefully lead to more consistent measurement. Our results suggest the possibility that respondents were not thinking about their changes in biking, scooting, or walking in the same way, which would make predicting these perceived changes challenging.

There are still interesting conclusions to be made from the models. First, bike share may have a different effect than scooter share on a user's perceived mental wellness. While the effects are uncertain, the model results showed that bike share would have a positive effect on a user's perceived mental wellness that is stronger for the first few minutes per day of use on average with diminishing returns the longer bike share is used. Scooter share on the other hand, is unlikely to have much of an effect on mental wellness based on how long a person uses it per day on average, but any effect is predicted to be a little negative and decrease one's perceived mental wellness. This is an interesting result: the promotion of active travel for its potential mental wellness benefits may produce noticeable differences in the effect by mode. The difference between the effects by mode, warrants further study to determine if this is a result of the AMP project – how the questions were designed and how participants were selected – or if this result is valid more generally.

Second, model results for perceived safety showed that bike share is perceived to be safer than scooter share. There is uncertainty in the predictions, so the difference between the perceived safety of bike share and scooter share may not always present itself. Unlike with mental wellness, the perceived safety of shared micromobility is not predicted to improve with increases in daily use of bike share or scooter share. Instead, longer term exposure to using these services over six months predicts that the user will perceive shared micromobility to be safer. Future work that measures a user's perceptions over time as they become more experienced with shared micromobility would help to determine if this result holds.

Third, users are predicted to increase their perceived changes in physical activity as a result of riding scooter share longer per day, but not for riding bike share. As scooter share itself does not provide significant physical activity benefits compared to bicycling or walking, it is interesting that users perceive increases in their biking, scooting, or walking as a result of riding. Perhaps that while scooter share trips themselves are not physically demanding, the trips may encourage users to introduce more activity into their routines in other ways. One pathway to increased physical activity that could not be explored with the AMP data is the potential for longer distance trips being made with electric devices that would have otherwise been shorter distance trips. Although electric devices require less physical activity to operate, they may also encourage users to make trips to destinations farther away than they would have traveled by walking or conventional bicycle. This was not possible to measure with the data from the AMP project, and it is a possibility that could be explored with future research.

It is interesting that the city-level variation was not as drastic as the person-level variation across all three studies. Similarly, when selecting network and weather predictors and clustering these values, the results of this clustering showed that participants did not experience a very diverse collection of environments. Because this study was focused on the effects of shared micromobility, the trips made on these shared micromobility devices are always contained within the operator's service boundaries. These service areas do not encompass entire cities or metro areas; they are usually confined to the busier, denser areas of cities, such as the downtown or financial and tourism districts. A consequence of this is that the areas participants were able to ride in were more likely to be relatively homogenous despite being in any of the dozens of cities across the United States, due to these urban cores across the country having very similar urban designs and gridded, car-centric street networks over generally flatter terrain. Additionally, the study only encompassed trips during Summer 2022, meaning that the weather was unlikely to vary within a city or even across cities as much as it would during the winter, when some areas of the United States are still very warm, such as Phoenix, Arizona, and others are very cold, like in New York City, New York.

The city-level variation not being very drastic suggests that studies for shared micromobility in the United States are generalizable. It may very well be true that the findings of a shared micromobility study in Washington, D.C., apply to other shared micromobility systems across the country. Instead, the characteristics of the participants themselves may be more important than the study location. Future work should endeavor to collect richer information about individuals, which may be more relevant for perceived changes in mental and physical wellness than the characteristics of their environments.

The results of this dissertation demonstrated the potential for shared micromobility use to have a positive effect on the perceived mental wellness of its user. The results also showed that it is possible for users to perceive these systems as safer the longer they are acquainted with them, and that users will perceive themselves to be more active after using micromobility. Mental wellness, safety, and physical activity are all important indicators of one's health, and shared micromobility use has shown to be a potential option for people looking to make improvements in these areas of their health as they introduce shared micromobility as an alternative to other travel modes.

An ideal study would build on the AMP study and this dissertation by combining measures of perceived mental and physical wellness with other objective measures, such as from physiological metrics from smartwatches. Longitudinal or panel data would enable researchers to observe how individuals' perceived wellness changes over time with their use of shared micromobility. Expanding data collection beyond the summer season, internationally, and to non-users or infrequent users of shared micromobility would provide a broader picture of perceived wellness and improve generalizability. A study that implements some of these improvements would help identify causal pathways and provide a stronger understanding of the range of health impacts of shared micromobility use.