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Analyzing the Impacts of a Successful Diffusion of Shared E-Scooters and Other Micromobility Devices and Efficient Management Strategies for Successful Operations in Illinois

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16. Abstract

Active transportation can play an important role in promoting more physically active and positive public health outcomes. While walking and biking provide significant physical health benefits, their modal share remains low. As a new form of micromobility service, shared e-scooters can enhance the suite of options available in cities to promote active transportation and fill in the gaps when walking or biking are not preferred. Although e-scooters show potential as a mode of transportation, it is unclear whether people will adopt the technology for everyday use. Furthermore, shared micromobility (e.g., electric scooters) is gaining attention as a complementary mode to public transit and is expected to offer a solution to access/egress for public transit. However, few studies have analyzed integrated usage of shared e-scooters and public transit systems while using panel data to measure spatial and temporal characteristics. This study aims to examine the adoption and frequency of shared e-scooter usage and provide policy implementation. To do so, the researchers launched a survey in the Chicago region in late 2020 and collected a rich data set that includes residents' sociodemographic details and frequency of shared e-scooter use. To characterize the frequency, the researchers used an ordered probit structure. The findings show that respondents who are male, low income, Millennials and Generation Z, or do not have a vehicle are associated with a higher frequency of shared e-scooter use. Furthermore, this study utilizes shared e-scooter trips for a 35-day measurement period from 10 shared e-scooter operators in Chicago, where the researchers used a random-parameter negative binomial modeling approach to analyze panel effects. The findings highlight the critical role of spatial and temporal characteristics in the integration of shared e-scooters with transit.

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We would like to thank Mr. Mark Bennett and Mr. Sean Wiedel from the Chicago Department of Transportation for their valuable contributions to this study. We would like to acknowledge Lime, Spin, and Bird as e-scooter vendors and for distributing the questionnaire among their registered users. In addition, we wish to thank Chicago's Regional Transportation Authority (RTA) and the Illinois Department of Transportation (IDOT), who reviewed the survey questionnaire during the planning stage.

Members of the Technical Review Panel (TRP) were the following:

- Charles Abraham, TRP Chair, IDOT
- Ken Runkle, TRP Co-chair, IDOT
- James Garner, Pace Suburban Bus
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The contents of this report reflect the view of the authors, who are responsible for the facts and the accuracy of the data presented herein. The contents do not necessarily reflect the official views or policies of the Illinois Center for Transportation, the Illinois Department of Transportation, or the Federal Highway Administration. This report does not constitute a standard, specification, or regulation.

EXECUTIVE SUMMARY

Dockless electric scooters (e-scooters) are one of the latest micromobility options to appear on our streets. As a burgeoning field, micromobility companies have had varied success as they began to operate in cities across the world—predominantly originating in China. E-scooters join other micromobility modes, such as dockless, nonelectric bikes as well as docked and dockless electric bikes (e-bikes). This shared body of research on the impact of micromobility modes and user travel behavior has primarily focused on bikes and e-bikes because they were the first modes to begin operation. They have shared characteristics with e-scooters, however, that allow much of the foundational work on micromobility to guide further research on e-scooters. This report aims to further the body of work specific to e-scooter usage. The researchers consider existing micromobility literature and apply it to understanding usage patterns and travel behavior within data collected over the course of two trial periods in Chicago.

Pilot programs for e-scooters have been conducted in cities around the United States, such as programs in Austin (Texas) and Portland (Oregon), or the pilot program that the researchers assisted with in Chicago. The purpose of these programs is to understand usage patterns of potential users and optimal deployment strategies for fleet operators to maintain accessibility for travelers while remaining financially sustainable.

Micromobility modes are a promising feeder mode for public transportation, supplementing city transit and increasing its accessibility to all riders—that is, the greater the adoption of these new modes, the more accessible and efficient any public transit system could become. Usage patterns and individual characteristics of early adopters are used to understanding the adoption and diffusion of this mode. Widespread adoption is generally city-dependent, relying on characteristics of a city's public transit and distributions of travelers performing commute versus non-commute trips. To understand the temporal characteristics of e-scooter usage (peak travel times), the literature indicates that researchers must understand how the development of the built environment affects travelers as well the role of educational campaigns and incentive-based programs initiated by city planners and e-scooter operators.

Collaboration between service operators and local transit authorities is highlighted as a means for planners to ensure that policy goals surrounding equity are met and for operators to ensure both their development and finances are sustainable. Collaboration allows standardized data collection among operators, such as trip origins and destinations, trip durations, and travel times. This planning is necessary to ensure that vehicle fleets are adequately distributed and that designated priority areas of each city maintain a minimum level of accessibility. Intelligent fleet distribution will distribute vehicles where and when they are needed. The literature demonstrates that intelligent fleet distribution has improved ridership, increased accessibility, and ensured the walkability and safety of the pedestrian environment.

The research team designed a survey to understand the characteristics of shared e-scooter users in Chicago and the benefits of promoting shared e-scooters in the region. They collaborated with the Chicago Department of Transportation to email a survey to e-scooter users within the Chicago metropolitan area. They also asked e-scooter operators to distribute the survey. Over the course of two collection periods in which the researchers piloted e-scooters in the city, they received 2,400 responses from users representing three regional operators: Bird, Lime, and Spin. The survey was structured to collect sociodemographic information, e-scooter usage behavior, and attitudes and preferences toward the mode. The researchers identified several equity groups within the population and then used this data to understand their behaviors and preferences. The groups included riders who were black or African American, low income, had lower education levels, and who lived within an Equity Priority Area (a designated region of Chicago that was identified as being underserved by transit).

The groups that constituted the largest portion of responses were young adults (aged 25 to 34), white riders, riders with higher education levels, and medium- to high-income riders. This report includes all respondents in the overall response rate for comparison between each identified equity group. Generally, these equity groups reported proportionally more frequent e-scooter usage and interaction with mass transit. Conversely, they also reported having to travel longer distances more frequently to pick up an e-scooter. The results of this data highlight the importance of cooperation with operators and enforcement by regional planning agencies to ensure equity goals are met.

With the ongoing COVID-19 pandemic, people are increasingly leading sedentary lifestyles and relying more on personal vehicles than previously used active modes or mass transit. The adoption and diffusion of e-scooters and other active modes presents an opportunity to promote modal shifts from car-based travelling. This study is an analysis of users' travel behavior during the second pilot period for e-scooters in Chicago, between November and December 2020. The researchers used an ordered probit model to characterize the individual, socioeconomic, and environmental factors that affect the ranked usage frequency responses of travelers.

Regarding individual characteristics, the researchers found that respondents who identified as white, low income, male, or younger than 34 were more likely to use e-scooters. The researchers inferred from this, in agreement with existing literature, that white people generally have higher access to e-scooters based on operators' fleet distribution. Low-income households having higher e-scooter usage can be understood by a higher reliance on mass transit, as there is a strong relationship between lower household income and lower vehicle ownership. The impact of gender on active mode choice was studied in the literature, and the research team's findings agreed that respondents who identify as male are more likely to use e-scooters than those who identify as female, which is likely related to differences in the perception of safety of this travel mode. The increased likelihood of younger respondents to use e-scooters over older respondents can be explained by the generational likelihood of adapting new technologies, as these active modes generally require associated applications and integration with smartphones. Additional findings included that respondents who were a part of reduced transit fare programs and those who lived in areas with high transit density were more likely to take e-scooters. These findings are in good agreement with existing literature on micromobility integration with public transit, as both respondent groups are also more likely to take public transit.

Modelling the frequency of micromobility integration with public transit is a current challenge for researchers, as there are issues with the type and quality of collected data as well as with data collection standards between operators. Promoting e-scooters as a feeder mode for transit faces these same challenges, where researchers must consider the spatial and temporal characteristics of traveler behavior and fleet distribution throughout a city. Data collection is reported on a set time interval through a GPS unit on each e-scooter, where collection is paused while a vehicle is rented by a traveler. The research team gathered trip data for over 100,000 e-scooter trips and analyzed trip start and end times as well as locations relative to public transit stations in the city of Chicago. A buffer region was defined around transit stations, where e-scooter trips that ended within the region were classified as access trips and e-scooter trips that began within the region were counted as egress trips.

Weather, development and land use, and perceptions of safety were the largest considerations that affected e-scooter integration with transit. Due to the time of year, weather that was deemed too cold or too humid negatively impacted both the use of the mode and transit integration. Multimodal links, such as bikeways, and a high density of office land use in areas around transit stations had a large, positive impact on integration. Conversely, the total number of vehicle accidents near a transit station negatively affected transit integration; the researchers understood this as a proxy for road safety and how it related to riders' perception of safety on a road, such as while using a dedicated bike lane. Some characteristics that describe e-scooter integration with transit are more intertwined, such as the positive impact that higher activity density has during peak travel times.

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CHAPTER 1: INTRODUCTION

Promoting micromobility is key to reducing the modal share of car-based trips. Empirical evidence shows that most car-based trips in the United States are short enough that people can alternatively perform them using micromobility options, if the barriers to switching from a transportation mode as comfortable as private cars are resolved (Zarif et al., 2019). As a practical solution, the literature suggests integrating various micromobility options, including docked bike-sharing programs such as Divvy bikes in the city of Chicago (Fu & Farber, 2017; Gu et al., 2019; Li et al., 2019).

Walking and biking, as the two most active micromobility options, provide noticeable health benefits; yet, their modal share remains understandably low, partially given people's various physical limitations. As a new form of micromobility service, the shared electric scooter (e-scooter) service couples ease of use for performing short- to medium- distance trips with many of the advantages of walking and biking. Unlike docked shared bikes and other micromobility options, the shared e-scooter system has given its riders flexible pick-up and drop-off locations. Although e-scooter service shows potential, it is not clear yet whether individuals will adopt it for everyday use.

Public perceptions of micromobility usage are a topic for many cities. A survey in Austin, Texas, reached over 9,500 people and queried their usage of e-bikes and e-scooters as well as their perceptions of the technologies as riders and non-riders (City of Austin, 2019). Of the participants in the Austin survey, 35% indicated they had never used micromobility services and did not plan to do so, but approximately 37% indicated having used e-scooters specifically at some point (City of Austin, 2019). E-scooters were consistently ranked higher than e-bikes on all surveyed feedback topics, including comfort, pricing, availability, convenience, and responsiveness (City of Austin, 2019). For riders in Austin, 96% of respondents indicated they have used a micromobility service at least once for recreation and 25% indicated they have used a micromobility service to travel to or from school at least once (City of Austin, 2019). However, 9.6% of respondents (922 people) indicated that commuting was their most frequent trip purpose, which is a respondent group that should be targeted (City of Austin, 2019).

There are prospects of future studies, such as in Des Moines, Iowa and Portland, Oregon. The regional transit authority and metropolitan planning organization in the Des Moines area (DART and MPO, respectively) are collaborating with various e-scooter operators to survey, plan, and develop the micromobility service in the region (Des Moines City Council, 2019). The MPO has enacted a plan by which they will develop pilot programs, but more fact finding and surveying is needed before recommendations can be made.

The pilot program enacted by the Portland Bureau of Transportation (2018) heavily involved collaboration between e-scooter companies and the bureau to ensure policy goals relating to accessibility, equity, and data gathering were met. All participating companies were required to standardize trip data, available real-time along with origin-destination (O-D) and route data. For the duration of the pilot, over 700,000 trips were made and most Portlanders viewed the services positively; 62% overall, 71% from residents under 35, 74% from people of color, and 66% from residents who identified as low income (Portland Bureau of Transportation, 2018). Though there was a large initiative for education and public engagement during the pilot program, there were difficulties with instructing riders on safety and legal guidelines as well as requiring e-scooter companies to meet equity and accessibility targets (Portland Bureau of Transportation, 2018).

Motor-driven cycles, also known as mopeds, are another form of shared micromobility that is gaining growing attention in the literature and cities worldwide. The District Department of Transportation launched a pilot program in Washington, D.C. to allow providers to offer shared moped services, provided they follow the required conditions. Those conditions required moped riders to follow current laws related to the operation of mopeds such as wearing a helmet, possessing a valid driver's license, and never riding on sidewalks and bike lanes (District Department of Transportation, 2021). Aguilera-García et al. (2021) showed that males, young adults, people with a high education level, and people in inner urban areas are prone to using shared mopeds more frequently. Moreover, age, occupation, and income are among influential factors affecting the future adoption of shared mopeds in urban areas. The authors also found that the availability of shared moped services may reduce the use of personal vehicles, resulting in less congestion in urban areas. However, they highlighted that e-mopeds may also capture demand from public transit systems and other forms of active modes. Accordingly, the net impact of e-mopeds on urban sustainability should be investigated.

CHAPTER 2: LITERATURE REVIEW

LESSONS FROM THE LITERATURE ON SHARED E-SCOOTER MOBILITY

A limited but growing number of studies have analyzed travel behavior using a shared electric scooter. Reviewing the existing transportation studies, Degele et al. (2018) grouped shared e-scooter customers into four clusters based on a dataset of e-scooter providers in Germany. The first cluster, “power users,” were highly active and inclined to use shared e-scooters on weekdays. The second and third clusters were casual users who were Generation X+ (40 years old or more) and Generation Y (approximately 28 years old), respectively. Both customer clusters used shared e-scooters presumably for leisure activities, because they rented scooters irregularly, but mostly on weekends. The last cluster, “one-time users,” adopted shared e-scooters once and had longer travel times and distances than the other clusters.

McKenzie (2019) investigated the similarities and differences between existing docked bike-sharing and a new dockless e-scooter service in Washington, D.C. They found that riders used these two services for different purposes. Riders usually used member bike sharing rather than dockless e-scooters in Washington, D.C. to get to and from work. Zhou et al. (2018) found that dockless bike-sharing services had caused a modal shift, decreasing metro ridership in Shanghai, China. Mooney et al. (2019) found that although the shared dockless bike program in Seattle had promising spatial equity characteristics in the region, neighborhoods with more educated residents had slightly more bikes.

Smith and Schwieterman (2019) used information downloaded via real-time data streams made available via operator-specific application programming interfaces (APIs) to analyze one day of Chicago’s e-scooter pilot program. The City of Chicago conducted this pilot program between June 15, 2019, and October 15, 2019. They observed that shared e-scooter trips were widely spread throughout the pilot region with an average trip distance of two miles. Commuters used shared e-scooters for transit access and egress since shared e-scooter usage reached its peak near the start of the morning rush and toward the end of the evening rush. Following this study, Smith (2020) used the same data and suggested that the shared e-scooter program can potentially decrease people’s travel times in Chicago. According to Smith (2020), between 24% and 29% of considered trips were quicker given shared e-scooter availability compared to trips involving walking and public transit alone in most neighborhoods within the e-scooter pilot area.

LESSONS FROM THE LITERATURE ON SHARED MICROMOBILITY

Because the current literature on shared e-scooter mobility is minimal, the research team focused on the literature of other shared micromobility options available in the transportation network. This helped the researchers evaluate to what extent other shared micromobility options successfully achieved their goals. The researchers may then incorporate these successful strategies into this study’s policy implementation.

The research team categorized the research stream on travel-behavior aspects of shared micromobility into three groups (please refer to Figure 1):

- Studies focusing on shared micromobility usage patterns. These studies seek to identify and compare the spatial and temporal shared micromobility usage patterns in cities using micromobility trip records for a specific period. This group of studies will help the research team extract the method used for analyzing spatial and temporal differences in the distribution of micromobility trips. The research team shall also analyze factors that may affect shared e-scooter usage.
- Studies focusing on integrating micromobility with the transit system. The newly prevailing shared e-scooter system provides a viable solution to the first- and last-mile problem and connects trip O-D to the transit station. These studies use micromobility trip records to measure the amount of integration between the micromobility and transit systems, as well as explore how built environment attributes impact the integrated use of these systems in different conditions.
- Studies focusing on the adoption and diffusion behavior of micromobility options. These studies seek to characterize the behavior of adopting micromobility options in urban areas as an essential step in planning a more sustainable transportation system. The research team shall use this research stream to design a robust and comprehensive survey instrument covering various travel-behavior aspects of shared e-scooter users.

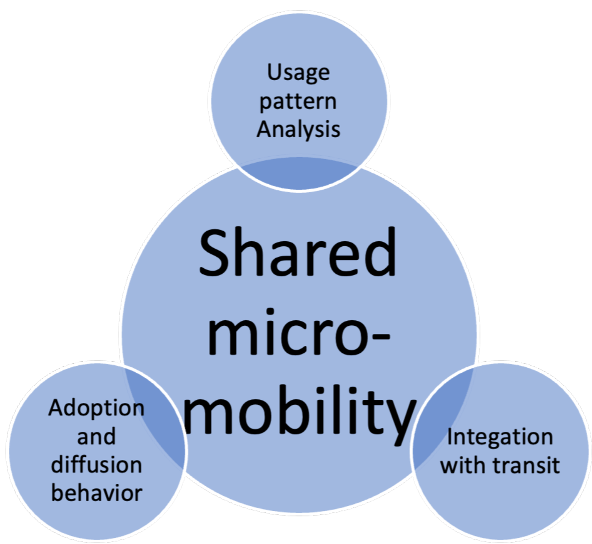

Figure 1. Diagram. Research stream on the travel-behavior aspects of shared micromobility.

Usage Pattern Analysis

Gathering usage data for shared micromobility options presents new challenges in data cleaning while offering new insights to trip O-D specification and travel behavior analysis. There is a wealth of research on dockless, electric motor-assisted, shared bike (e-bike) programs, which can guide study on the same areas for e-scooter usage analysis. Collected data on e-bike programs contain nonuniformities that prevent cleaning with traditional methods in which O-D data can be directly obtained (Li, 2019). Li (2019) explained that O-D data may not reflect the actual behavior of travelers because of the speeds e-bikes travel combined with a weak or inconsistent GPS signal (either due to depleted batteries or the frequency of data collection) and a lack of ride status. McKenzie (2019) addressed these issues by using information such as average trip duration and maximum speed to determine if a trip is genuine, whether the scooter is being charged, redistributed, or relocated by a non-rider.

The main factors for spatial and temporal differences, found in McKenzie (2019), were mixed land use along the route of the trip, the O-D traffic analysis zone, and program membership. Over 60% of trips in the McKenzie (2019) study originated and terminated in the same land-use type (e.g., residential to residential, commercial to commercial) and most trips originated from either commercial or public land-use types, with about 23% of all trips originating in a residential land-use type. Program membership (compared to casual riders) was also shown to have a striking difference in temporal use; essentially, riders with program memberships used the service around commute times far more frequently than casual riders (McKenzie, 2019).

Integration with Transit

The ability of micromobility options to integrate with transit in addressing the first-and-last-mile problem is well studied. Fong et al. (2019) shows that e-bikes and e-scooters greatly increase the range for all transit users and those with mixed modes, increasing the distance travelers are willing to travel between a parked car and transit or the distance to or between bus stops and train stations. Though, there are still challenges in promoting micromobility integration, especially for commuting. Micromobility integration with transit will likely be a necessary development as cities begin banning vehicles, such as some city centers, which are almost entirely pedestrianized. Micromobility options are vital for travelers, especially in cities with subpar transit options, but there is also potential for businesses to benefit from their development, as last-mile delivery comprises, on average, 28% of total shipping costs (Fong, 2019).

Adoption and Diffusion Behavior

The adoption of micromobility options faces many challenges in terms of development and deployment of vehicle fleets as well as spreading the use of these modes as a popular travel option. One hurdle to increasing the popularity of micromobility might be a matter of culture, where micromobility options have not existed for a long enough time to capture the attention of travelers as a legitimate mode (McKenzie, 2019).

For service operators, it will be necessary to identify the regions and time periods the vehicle fleet needs to be distributed, such as places in residential and commercial zones, within the catchment area of large transit hubs, and during peak travel hours (Guo & He, 2021). However, there needs to be direction to the fleet redistribution, as overcrowding busy metro areas with unused vehicles creates unwalkable environments (Guo & He, 2021; Gu, 2019).

The operation of dockless e-bikes and e-scooters is generally private and largely capital-driven; this creates challenges with regulatory governing bodies and problems with sustainable development, as the potential for fast growth can create problems with overcrowding and financial instability (Gu, 2019). For operators, Gu (2019) shows that being solvent is more determined by the expansion and availability of fleet supply, rather than by meeting user demand or regulatory policy. This can create situations where rapid expansion leads to harsh regulation, such as with the development of e-scooters in San Francisco (Fong, 2019). The solution to this supply-driven expansion will have to create alternate sustainable income for operators and will require future study (Gu, 2019).

CHAPTER 3: DATA REPORT

The researchers designed a survey to understand the characteristics of shared e-scooter users in Chicago and the benefits of promoting shared e-scooters in the region. Because the modal share of e-scooter users is meager, the researchers collaborated with the Chicago Department of Transportation to send the survey link to shared e-scooter users in the Chicago metro area. As part of this collaboration, the researchers asked shared e-scooter vendors (i.e., Lime, Spin, and Bird) to distribute the questionnaire among their registered users. After three weeks of data collection (between November 20 and December 15, 2020), the research team received 2,400 completed responses, representing users of all three e-scooter vendors.

The survey was structured to collect a rich set of information in the following areas: 1) sociodemographics such as residential location, age, gender, ethnicity, as well as economic factors such as job status and household income; 2) the frequency of using shared e-scooters in both phases of the program in Chicago; 3) users' attitudes and preferences toward using shared e-scooters, while accounting for individuals' transportation needs; 4) the impacts of shared e-scooters on individuals' health and well-being; and 4) the effect of shared e-scooters on individuals' mode-choice decision, especially for getting to/from transit stations. The researchers also asked several attitudinal questions to better understand what underlying factors form the intention of using shared e-scooters and how such factors contribute to the individuals' intentions to continue using this mode in the future. Moreover, the research team incorporated Google Maps API to collect respondents' approximate residential locations (i.e., the nearest intersection to their home address) in the questionnaire.

This study aims to explore how people perceive and use shared e-scooters. The results of this research are intended to not only evaluate the second e-scooter pilot program run in Chicago, but also help improve the benefits of shared e-scooters for users in the future.

USER SOCIODEMOGRAPHICS

Age, gender, and race are important characteristics of a population, and when completing the survey, users could record those characteristics and many others that may help describe the population of this study as a whole. Figure 2 presents the distribution of ages. The data show that most e-scooter users are young adults (i.e., 34 years or younger). The largest age bracket was that of 25 to 34 years of age, with 54% of users falling in that bracket. Around 18% of users reported their age between 18 and 24. Very few respondents were older than 45 years old.

The survey also asked for the user's gender, with the options being male, female, other, and prefer not to answer. Less than 3% of users marked their genders as "other" or "prefer not to answer." Figure 3 presents the proportion of male and female respondents among the remaining users. Nearly two-thirds (63%) of those who answered reported as male and 37.4% of respondents reported they were female.

Information on the respondents' races was also collected; the distribution is shown in Figure 4. Users had the option to choose white, black or African American, American Indian, Asian, Native Hawaiian or Pacific Islander, or other, where a race could be described. Three-quarters of the respondents selected that they were of Caucasian heritage, and only 11% selected black or African American. A very small amount (1%) of respondents reported they were American Indian or Native Hawaiian or Pacific Islander. Respondents could also indicate if they were of Hispanic or Latino heritage, and the results are shown in Figure 5. A small proportion (16%) of respondents were of Hispanic or Latino heritage, so overall, the respondents were not very diverse.

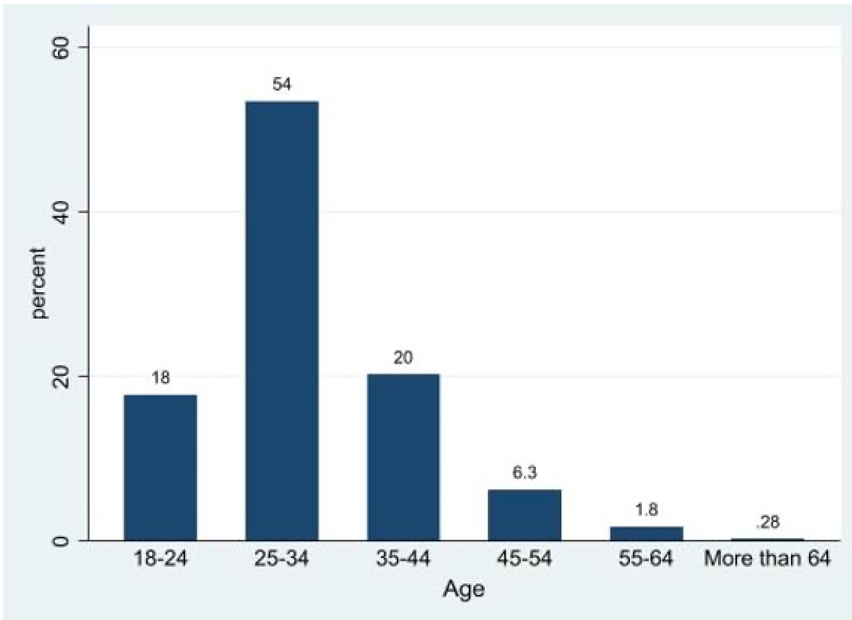

Figure 2. Bar plot. Distribution of respondents' age.

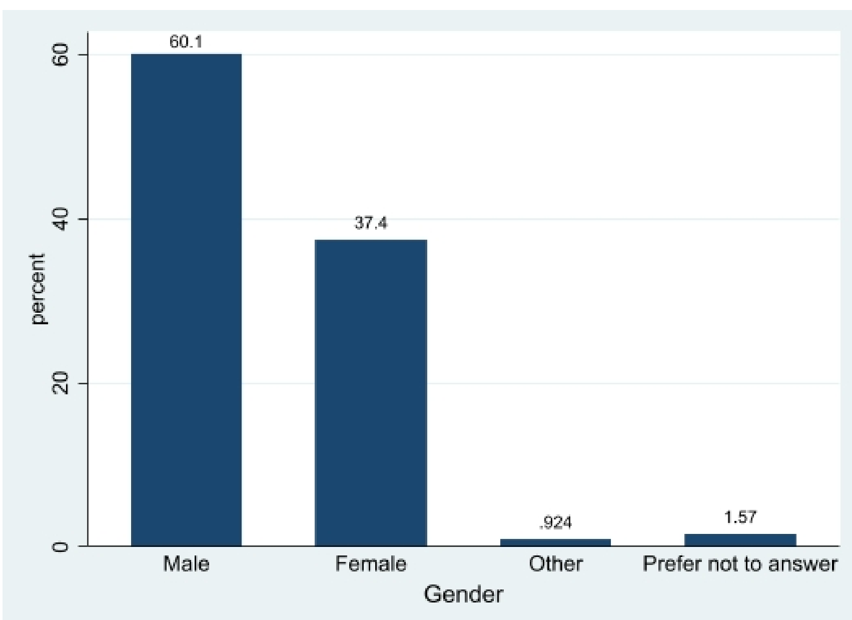

Figure 3. Bar plot. Distribution of respondents' gender.

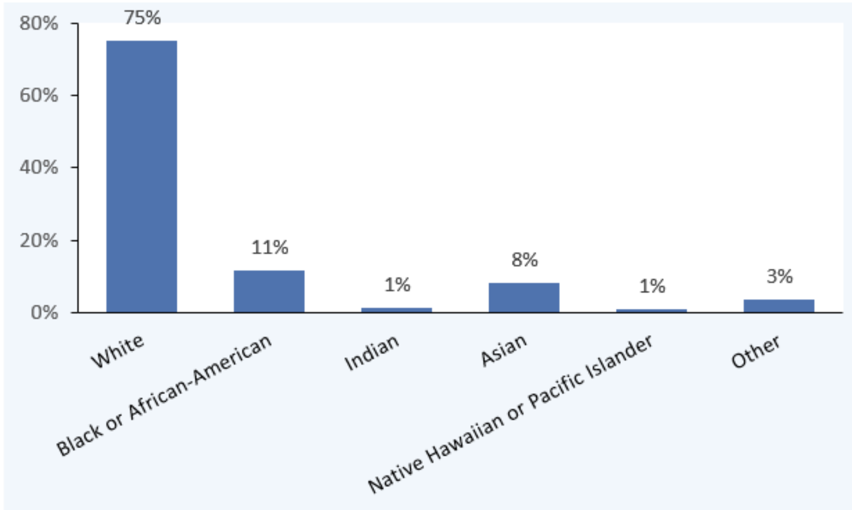

Figure 4. Bar plot. Distribution of respondents' race.

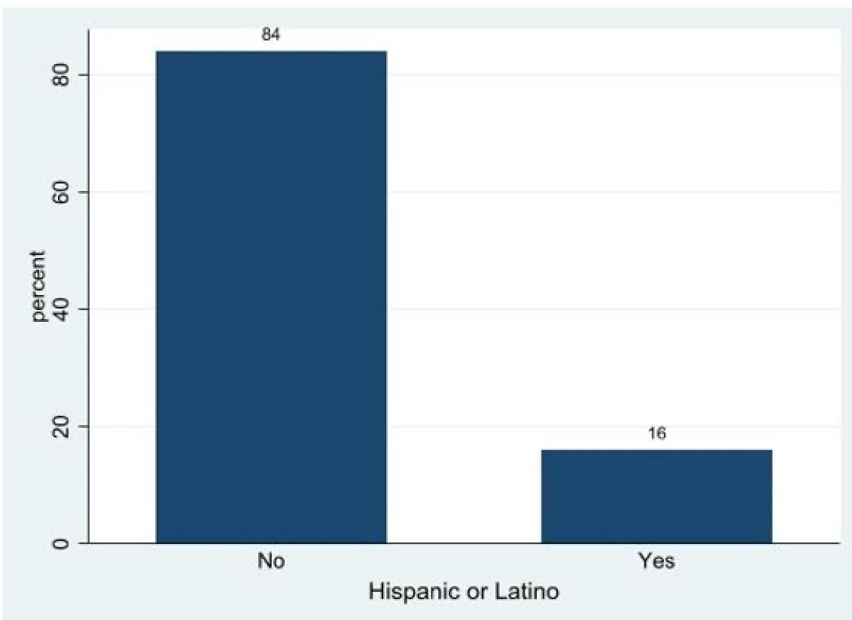

Figure 5. Bar plot. Distribution of respondents with Hispanic or Latino heritage.

Data on the education and household income of respondents were also collected (Figures 6 and 7, respectively). Nearly all respondents (around 93%) had completed high school and at least attended college in some capacity, and only 5.5% have a high school diploma or less. Overall, half of the respondents indicated that they have graduated with a bachelor's degree. The education levels can be related to the income of the respondents. One-third of respondents indicated that their entire household made between \$50,000 and \$100,000, while 32% indicated that their income was above \$100,000. Income, however, is not the greatest indicator of the wealth of a respondent, because household size is also an important factor. Looking at the data, one can see that the typical e-scooter user tends to be well educated and fairly wealthy.

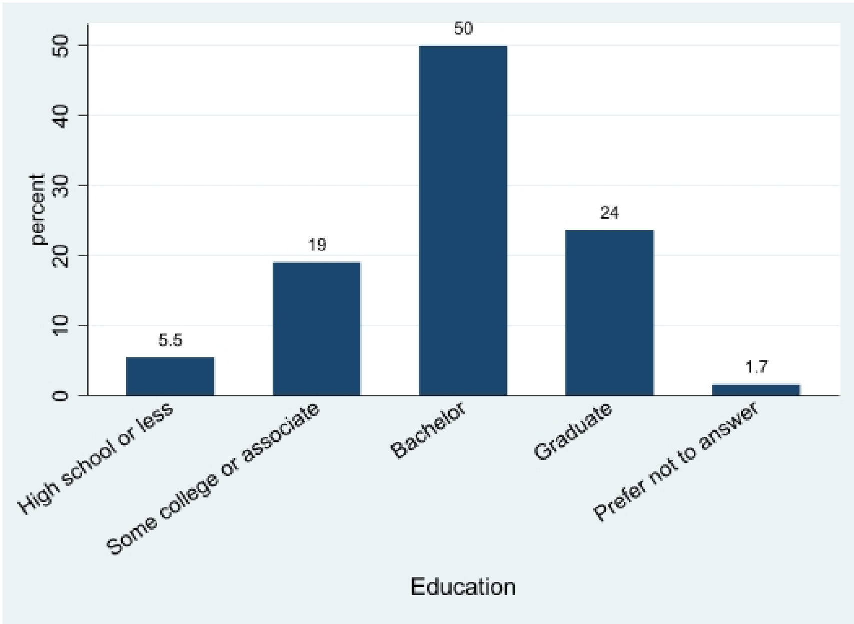

Figure 6. Bar plot. Distribution of respondents' education level.

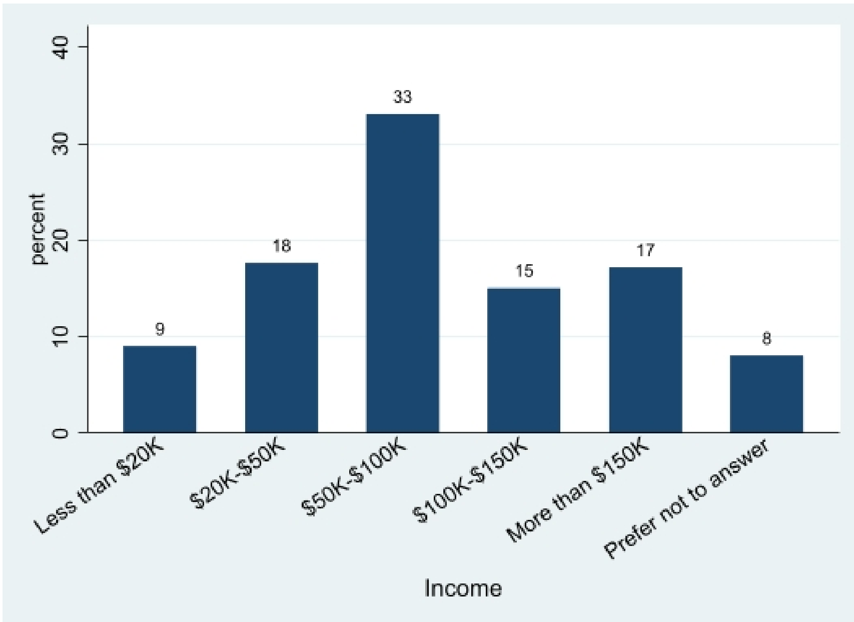

Figure 7. Bar plot. Distribution of respondents' income.

In addition, the survey asked respondents about the number of vehicles in their household, if they had a bike-share membership, and if they qualified for reduced transit fares. Figure 8 presents the responses for the number of vehicles per household. More than two-thirds (69%) of respondents have at least one vehicle in their household, while the remaining 31% do not have a vehicle. Although some respondents may not have any vehicles in their household, nearly all (90.3%) respondents have their driver's license, as seen in Figure 9.

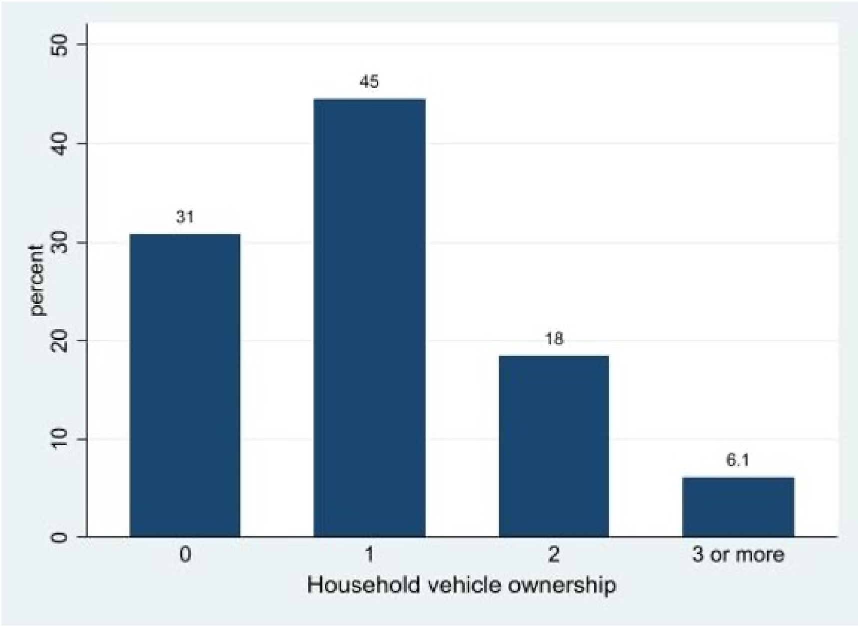

Figure 8. Bar plot. Distribution of respondents' household vehicle ownership.

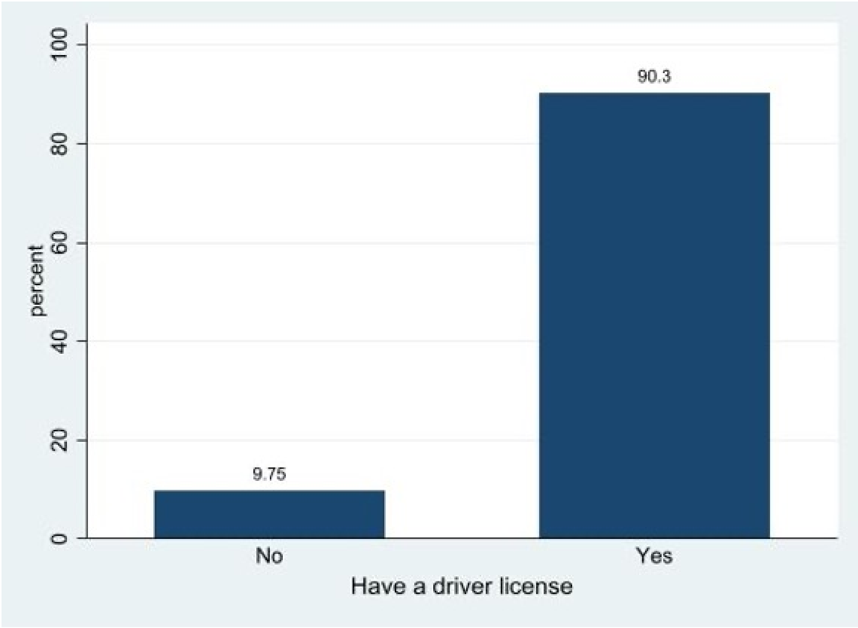

Figure 9. Bar plot. Distribution of respondents' driver's license status.

Some people may not need to drive to get to their desired location, as there are numerous different commuting options in the city. An oftentimes viable commuting mode is the use of shared bicycles provided by the bike-share company Divvy. The company offers single ride and daily passes or monthly memberships, and Figure 10 shows the popularity of the bike-share membership among the respondents. Around 23% of the respondents indicated they currently have a Divvy membership. While this statistic does not include those who purchase single ride or day passes as opposed to the membership, it still indicates considerable levels of micromobility diffusion into e-scooter users' lifestyles in the region.

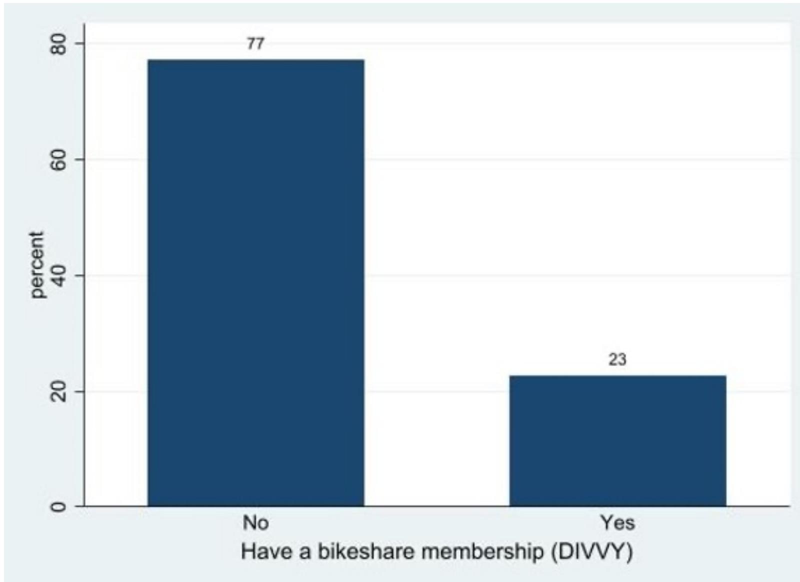

Figure 10. Bar plot. Distribution of respondents' bike-share membership.

Certain groups of transit users in Chicago are eligible for reduced or free transit fare (Figure 11). Young children as well as elementary and high school students are eligible for reduced fares, whereas active military personnel, disabled veterans, seniors, Medicare cardholders, and people with disabilities can be eligible for free transit. Of the respondents, only 9.1% qualified for this assistance. This is likely because not many respondents had disabilities, only 7.07% (Figure 12), and the typical user was older than 18 years old and younger than 45 years old.

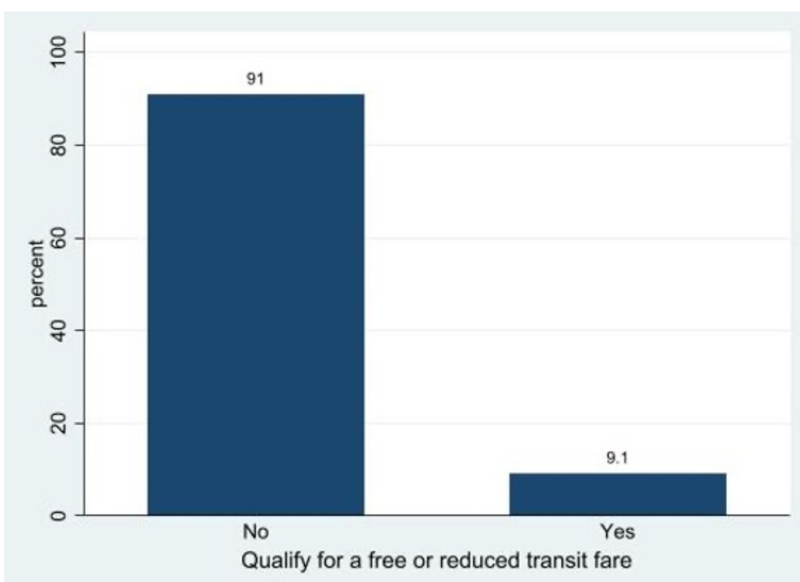

Figure 11. Bar plot. Distribution of respondents that qualify for reduced transit fare.

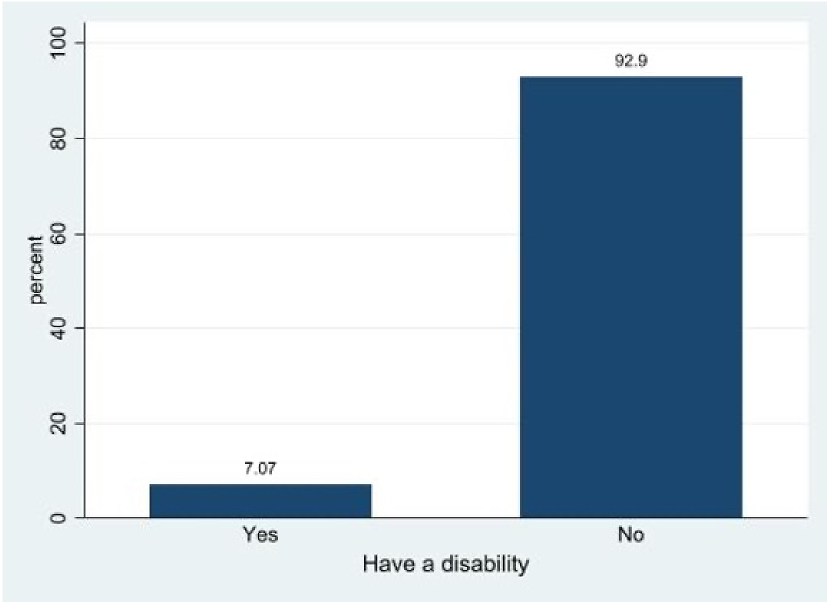

Figure 12. Bar plot. Distribution of respondents with disabilities.

Figure 13 shows the different exercise frequencies among respondents. Nearly three-quarters (71%) of respondents indicated they exercised at least two days per week. The frequency of exercise is distributed fairly evenly, with the frequency of two to three times per week being the exception at 36%. Other frequencies fell between 13% and 20% of the sample.

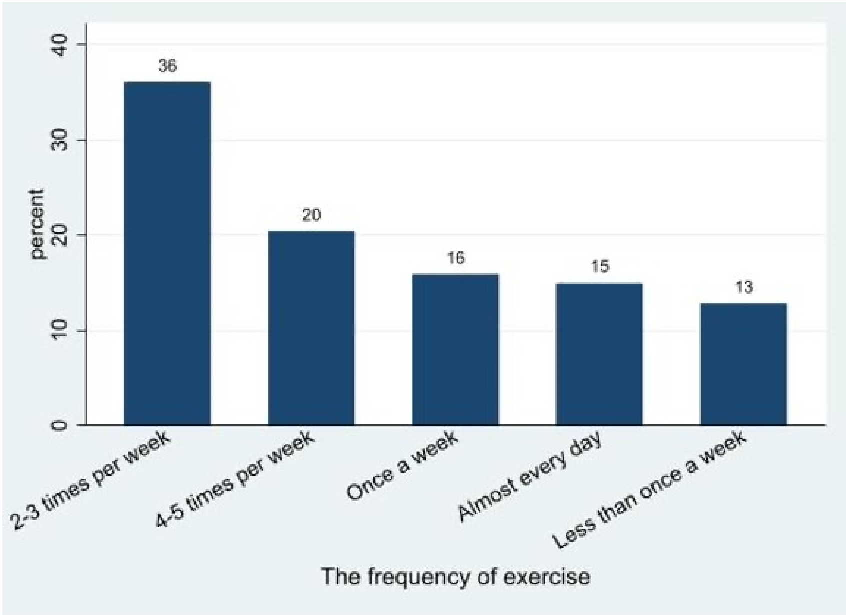

Figure 13. Bar plot. Distribution of respondents' exercise frequency.

E-SCOOTER USAGE PATTERN

The first e-scooter pilot program took place from June to October in 2019. This study not only looked at e-scooter use during October and November 2020, but also e-scooter use during the first pilot program. This report defines various respondent group categories for comparison; the study considers respondents who indicated that they were black or African American, low-income respondents who indicated that their household income is less than 200% of the poverty level in Illinois, those who live within the Equity Priority Area shown in Figure 14, and those who indicated that they held less than a bachelor's degree. These groups were defined in order to compare patterns of travel behavior and accessibility between interested population groups.

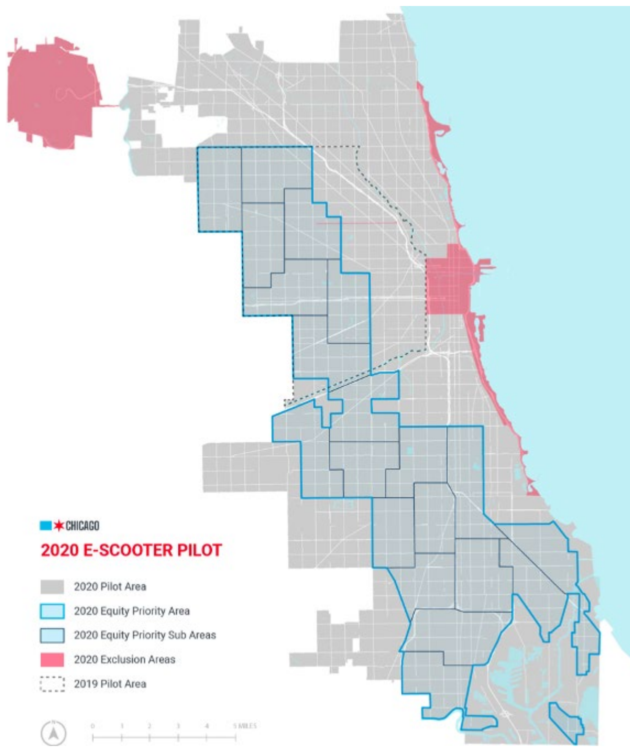

Figure 14. Map. Equity priority area (blue line) defined in City of Chicago (2020).

There were 793 respondents who reported that they participated in the first pilot, and none reported not using an e-scooter. This group included 698 respondents who would then also participate in the second pilot (Figure 15). With 2,166 total response records, 63.4% of respondents did not participate in the first pilot. Where respondents indicated less frequent usage in Figure 15, such as less than five times or only once, response rates among some respondent groups were less than the overall response for that pilot. Fewer respondents living in the priority area (7.1%) and respondents with lower education levels (5.1%) reported they tried e-scooters once compared to the overall response rate (10.5%). Black respondents had lower response rates for usage in the two to five trips range (22.9% compared to 40.5%). While black respondents reported less frequent low-usage or trial usage, they, along with respondents with lower education levels and those living in the priority area, constituted the largest groups that reported daily or almost daily usage (more than 10 trips).

Of the 2,070 respondents that participated in the second pilot, 22.8% of all respondents indicated they did not use an e-scooter during this period (Figure 16). However, there was a larger number of people, in both relative and absolute terms, who tried the e-scooter one or two to three times (45.4% in the second pilot compared to 30.8% in the first pilot). Though there was a lower proportion of respondents who indicated very frequent usage (more than 10 times) compared to the first pilot, interested respondent groups generally reported more frequent usage when compared with all respondents in this usage pattern.

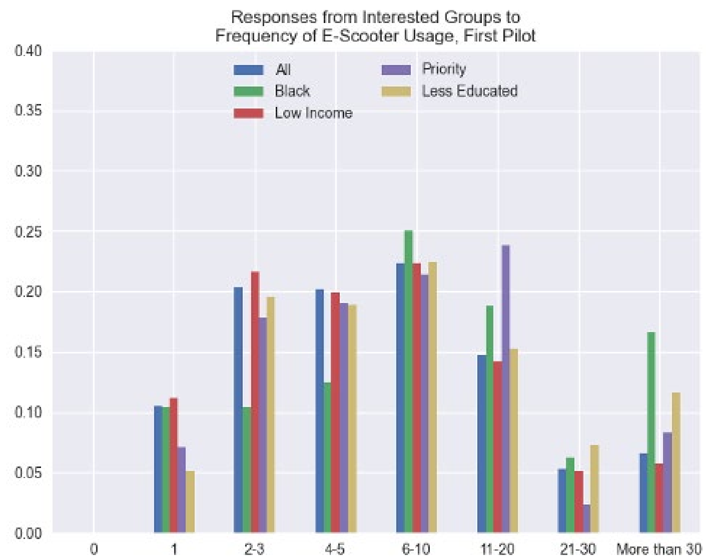

Figure 15. Clustered bar plot. E-scooter usage frequency in the first pilot.

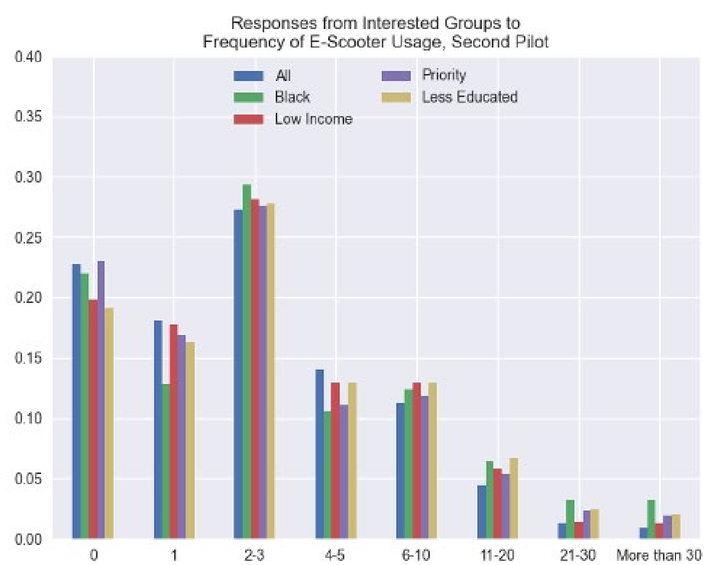

Figure 16. Clustered bar plot. E-scooter usage frequency in the second pilot.

A great benefit of e-scooters is the ability to use them in conjunction with other modes of transportation, specifically Chicago Transit Authority (CTA) buses and rails and Metra trains (Figure 17). Some respondents reported they took advantage of this benefit, but around two-thirds (64%) reported they did not. This lack of transit integration could be explained by the diminished ridership of transit during the COVID-19 pandemic, which could also explain the more frequent usage pattern from the second pilot (above in Figure 16). However, all groups of interest reported higher transit integration than the overall population, with the highest share of integration among respondents living in the priority area.

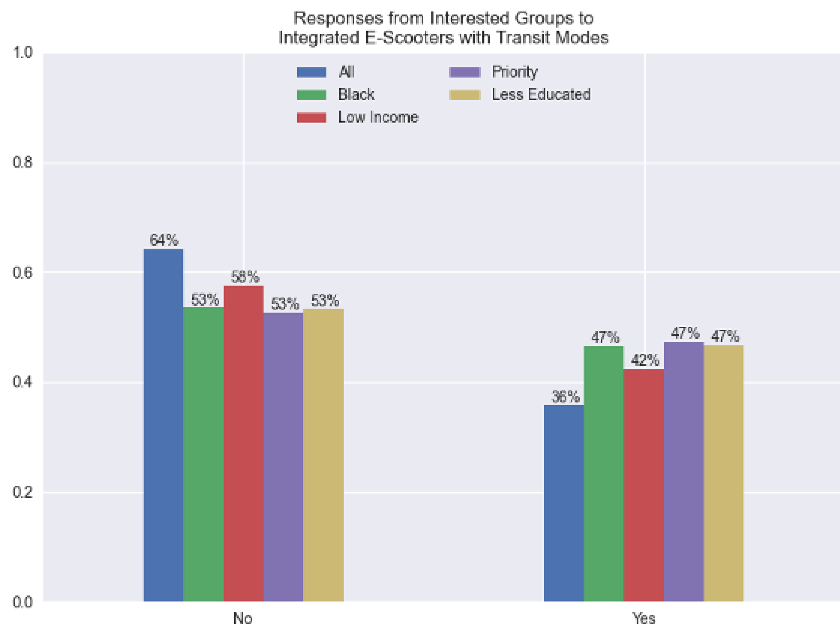

Figure 17. Clustered bar plot. How respondents integrated e-scooters with transit.

E-scooters also can be used to replace different modes of transportation throughout the city (Figure 18). More than one-third of respondents (39.5%) reported they would have walked to their destination if an e-scooter had not been available, while 29.5% would have traveled in a car (via ride-hailing, taxis, or personal vehicles). Substantially fewer respondents (11.6%) would have used mass transit (CTA buses and trains, Pace buses, or Metra trains). Respondent groups all reported a lower mode-replacement rate for ride-hailing and shared bike programs (Divvy) than the overall population and a higher mode-replacement rate for mass transit. Additionally, the presence of e-scooters facilitated some trips, specifically for black (7.0%) and less educated (5.8%) respondents compared to the overall population (4.5%), who would not have taken the trip at all.

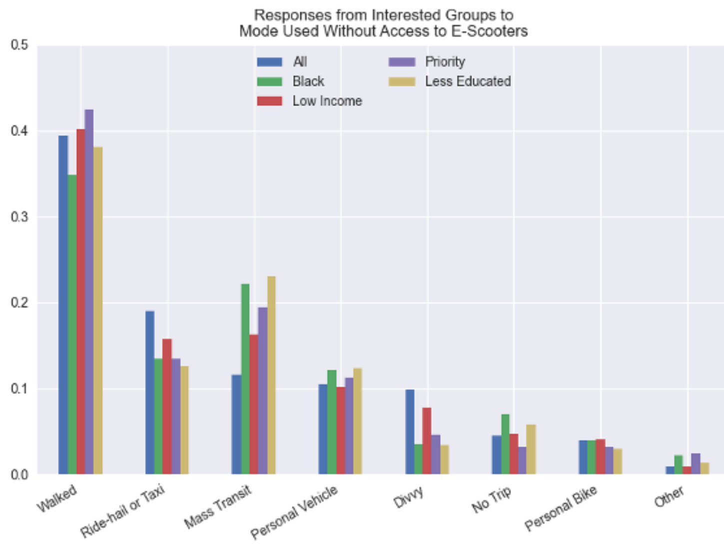

Figure 18. Clustered bar plot. Mode shift among respondents due to e-scooter usage.

TRANSPORT STYLES

Since this study occurred during the COVID-19 pandemic, many respondents may have altered their transportation habits. As a result, the use of some forms of transportation may be lower than normal. Therefore, to get a good understanding of how e-scooters are used, it is important to analyze the usage of transportation options before the pandemic (Table 1). Before the pandemic, around 88% of respondents would frequently walk to their destination. Mass transit was also common before the pandemic, with almost 70% of respondents using trains frequently and over half using the bus (compared to 49% reporting to frequently using a personal vehicle). E-scooters were not used as frequently as other transit and passenger vehicle options, with around 38% of respondents reporting that they used them sometimes or often, which is about as frequent as the respondents chose to take a personal bike.

Table 1. Frequency of Respondents' Use of Transport Options for Daily Travel during the First Pilot

Transport option	Never (%)	Seldom (%)	Frequently (%)
Personal vehicle	36.17	14.73	49.10
CTA bus	22.03	25.17	52.80
CTA rail	11.64	18.61	69.74
Metra rail	54.32	32.15	13.53
Pace bus	84.48	10.85	4.66
Ride-hailing (Uber and Lyft)	7.07	21.80	71.13
Carpool	69.56	17.92	12.52
Taxi	71.04	22.22	6.75
Walk	4.34	7.85	87.81
Personal bike	50.90	14.27	34.83
Shared bike (Divvy)	46.74	26.74	26.52
Shared e-scooter	30.53	31.92	37.55
Skateboard	92.42	4.62	2.96

The researchers can investigate pre-pandemic trip purposes, broken down by the response frequency of respondent groups in which the researchers are interested (Table 2). Responses indicating frequent use of mass transit are generally high, though each respondent group reports more frequent usage of CTA bus, Metra, and Pace than the overall response rate. Additionally, each of the groups reported more frequent usage of e-scooters than the overall group (43.9% for low income and 52.9% for less educated compared to 37.6% overall).

Table 2. Percentage of Respondents Who Indicated Frequently Using Transport Options for Daily Travel during the First Pilot

Transport Option	All (%)	Black (%)	Low Income (%)	Priority (%)	Less Education (%)
Personal vehicle	49.10	56.96	47.35	60.42	53.66
CTA bus	52.79	63.91	58.33	56.18	57.04
CTA rail	69.75	60.00	70.55	63.96	63.60
Metra rail	13.53	16.52	14.68	16.61	14.45
Pace bus	4.67	12.61	6.91	11.66	10.88
Ride-hailing (Uber and Lyft)	71.13	70.43	67.33	64.66	62.48
Carpool	12.52	24.35	15.53	18.02	18.20
Taxi	6.74	12.17	6.63	9.19	8.07
Walk	87.81	79.13	86.74	82.69	83.86
Personal bike	34.83	33.91	33.81	42.05	36.21
Shared bike (Divvy)	26.51	23.04	25.19	22.26	21.58
Shared e-scooter	37.55	49.57	43.94	48.06	52.91
Skateboard	2.96	5.65	4.45	5.65	6.94

The respondents were also asked about their transportation habits to connect to bus, train, and subway stations before e-scooters were introduced to Chicago (Table 3). Walking had the highest frequency of users, with 85% of respondents reporting they would frequently walk to connect to different transportation modes. Respondents also used ride-hailing services frequently (45.6%). Overall, active transportation methods had more frequent users, which is expected because many stations are short distances away from each other.

Table 3. How Frequently Respondents Used Various Transport Options to Travel to or from Mass Transit Before Shared E-Scooters Became Available

Transport Option	Never (%)	Seldom (%)	Frequently (%)
Personal vehicle	58.01	11.22	28.91
Ride-hailing (Uber and Lyft)	31.13	21.39	45.64
Carpool	75.06	12.38	10.72
Taxi	78.24	14.41	5.50
Walk	6.70	6.42	85.03
Personal bike	62.82	11.55	23.79
Shared bike (Divvy)	58.80	17.37	21.99
Skateboard	91.87	3.37	2.91

The researchers can investigate the breakdown by respondent group to determine how the presence of e-scooters could affect their respective travel behaviors (Table 4). Using a personal vehicle to connect to or from mass transit, for instance, was used more frequently among all respondent groups. The largest percentage was for black respondents: 47.0% compared to the 29.0% overall response rate. There is a similar trend for carpooling, where black respondents are twice as likely to have taken that mode frequently.

Table 4. Percentage of Respondents Who Indicated Frequently Using the Following Transport Options for Daily Travel during the First Pilot

Transport Option	All (%)	Black (%)	Low Income (%)	Priority (%)	Less Education (%)
Personal vehicle	28.91	46.96	32.10	42.05	40.53
Ride-hailing (Uber and Lyft)	45.64	52.61	49.05	47.00	46.72
Carpool	10.72	21.74	13.83	16.96	16.70
Taxi	5.50	13.04	5.87	9.54	7.32
Walk	85.03	73.04	84.28	77.39	77.67
Personal bike	23.79	28.26	26.70	34.63	28.33
Shared bike (Divvy)	21.99	20.00	23.01	19.43	20.26
Skateboard	2.91	5.22	4.45	6.71	6.75

Since there have been two pilot periods for shared e-scooters in Chicago, the purposes for using e-scooters may have changed (Table 5). During the first pilot, June to October 2019, respondents frequently reported using e-scooters for leisure and other activities. Another frequent use of e-scooters in the first pilot was transit. Around 59% of respondents frequently used e-scooters to avoid other transit options, and another 38% used them to connect to other transportation methods during transit. Despite frequent use by young people, not many respondents used e-scooters to get to school or class (10.7%).

Table 5. Respondent Frequency of Trip Purpose during the First Pilot

Purpose	Never (%)	Once (%)	Frequently (%)
Riding around and having fun	16.90	23.96	59.14
Avoiding using transit	26.36	14.63	59.01
Attending recreational activities (bar, theater, etc.)	22.70	14.88	62.42
Getting exercise	79.70	6.68	13.62
Visiting friends/relatives	33.04	15.89	51.07
Doing household errands	55.49	12.11	32.41
Eating meals outside of home	43.25	15.13	41.61
Getting to or from my parked vehicle	76.29	8.58	15.13
Getting to or from transit	48.80	13.11	38.08
Going to the workplace	64.44	8.70	26.86
Getting back from the workplace to home	64.56	7.31	28.12
Getting to or from school/class	85.37	3.91	10.72
Doing routine shopping (e.g., groceries)	62.30	11.60	26.11
All other shopping activities	61.16	9.96	28.87
Healthcare appointments	78.06	9.33	12.61

Separating the respondents by group and showing their response rate for the purpose of e-scooter trips during the first pilot (Table 6) will aid in understanding the role broader e-scooter programs might play in the travel behavior of these interested groups. Black and less educated respondents indicated more frequent e-scooter trips with the following purposes: having fun, avoiding transit, exercising, doing errands, connecting to or from transit, commuting to or from both work and school, all shopping activities, and attending healthcare appointments. This could indicate that e-scooters had the largest impact on improved mobility for these groups and facilitated trips to happen that otherwise would not have, given that black and less educated respondents were the largest groups to indicate “no trip” above in Figure 18.

Table 6. Percentage of Respondents Who Indicated Frequently Having a Given Trip Purpose during the First Pilot

Purpose	All (%)	Black (%)	Low Income (%)	Priority (%)	Less Education (%)
Riding around and having fun	59.14	73.33	62.57	58.49	72.41
Avoiding using transit	59.02	70.00	60.29	64.15	67.24
Attending recreational activities (bar, theater, etc.)	62.42	61.67	56.57	56.60	56.90
Getting exercise	13.62	31.67	16.57	18.87	30.46
Visiting friends/relatives	51.07	58.33	51.71	45.28	58.05
Doing household errands	32.41	51.67	37.43	34.91	45.98
Eating meals outside of home	41.61	50.00	40.57	36.79	45.98
Getting to or from my parked vehicle	15.13	31.67	18.57	21.70	28.16
Getting to or from transit	38.08	53.33	44.57	47.17	53.45
Going to the workplace	26.86	48.33	34.29	36.79	41.38
Getting back from the workplace to home	28.12	41.67	34.00	38.68	41.38
Getting to or from school/class	10.72	23.33	16.86	11.32	21.26
Doing routine shopping (e.g., groceries)	26.10	43.33	31.14	27.36	41.38
All other shopping activities	28.88	50.00	32.57	30.19	44.83
Healthcare appointments	12.61	26.67	16.57	13.21	20.11

Since this study took place during the COVID-19 pandemic, many purposes may have lower responses than usual (Table 7). For example, the number of respondents who reported that they frequently use e-scooters to attend recreational activities dropped by more than 31%. Nearly all trip purposes have at least 50% of respondents answering “never,” and only five have 30% or more of respondents answering “frequently.” Overall, the pandemic greatly limited the use of e-scooters for recreation and travel.

The second pilot period serves as an opportunity to gauge how lockdowns impact overall travel behavior, and separating respondents by interested groups allows us to measure disparity in this impact (Table 8). Even with overall decreased travel, black and less educated respondents still reported the same trip purposes more frequently than the overall response rate when compared to the first pilot (Table 6).

Table 7. Respondent Frequency of Trip Purpose during the Second Pilot

Purpose	Never (%)	Once (%)	Frequently (%)
Riding around and having fun	44.83	21.98	33.18
Avoiding transit because of concerns about COVID-19	45.65	10.97	43.38
Avoiding using transit for other reasons	57.54	9.32	33.14
Attending recreational activities (bar, theater, etc.)	56.09	13.33	30.58
Getting exercise	80.82	5.65	13.53
Visiting friends/relatives	52.17	13.91	33.92
Doing household errands	57.54	12.90	29.56
Eating meals outside of home	64.15	11.55	24.30
Getting to or from my parked vehicle	83.91	5.41	10.68
Getting to or from transit	72.71	10.00	17.30
Going to the workplace	78.26	5.65	16.09
Getting back from the workplace to home	78.16	5.75	16.09
Going to school	91.88	2.32	5.80
Getting back from school to home	91.79	2.37	5.85
Doing routine shopping (e.g., groceries)	65.41	11.59	22.99
All other shopping activities	65.27	11.11	23.62
Healthcare appointments	80.72	8.79	10.48

Table 8. Percentage of Respondents Who Indicated Frequently Having a Given Trip Purpose during the Second Pilot

Purpose	All (%)	Black (%)	Low Income (%)	Priority (%)	Less Education (%)
Riding around and having fun	33.19	47.71	39.52	39.46	47.69
Avoiding transit because of concerns about COVID-19	43.38	48.62	47.70	39.85	49.30
Avoiding using transit for other reasons	33.14	46.33	37.03	39.46	42.66
Attending recreational activities (bar, theater, etc.)	30.58	33.03	32.53	29.89	31.59
Getting exercise	13.53	31.65	17.27	25.67	25.55
Visiting friends/relatives	33.91	40.83	37.92	37.16	38.63
Doing household errands	29.57	43.12	32.34	32.57	38.83
Eating meals outside of home	24.30	33.49	25.95	30.27	30.38
Getting to or from my parked vehicle	10.68	23.39	14.27	18.39	19.72
Getting to or from transit	17.29	30.73	23.05	27.97	31.19
Going to the workplace	16.09	28.44	22.65	24.52	30.99
Getting back from the workplace to home	16.09	26.61	22.65	25.67	30.38
Going to school	5.80	15.14	8.58	9.20	13.08
Getting back from school to home	5.85	13.76	8.58	10.34	12.68
Doing routine shopping (e.g., groceries)	23.00	33.94	27.15	24.90	31.59
All other shopping activities	23.62	33.94	26.85	25.67	32.80
Healthcare appointments	10.48	17.43	13.17	11.49	14.49

Respondents were also able to report their experiences with the distances the nearest available e-scooter was to them during this study (Table 9). Respondents reported they typically did not have to walk for more than 5 minutes to pick up an e-scooter; however, around 13% of respondents had at least one occurrence of having to walk more than 10 minutes to find an e-scooter. The most frequent length of time a respondent would have to walk is 2 minutes or less, with 55.3% reporting that time as occurring frequently.

Table 9. How Frequently Respondents Faced the Following Situations during the Second Pilot

Situation	Never (%)	Once (%)	Frequently (%)
Walk for less than 2 minutes to pick it up	26.43	18.31	55.27
Walk for 2 to 5 minutes to pick it up	37.73	17.92	44.35
Walk for 5 to 7 minutes to pick it up	64.30	13.33	22.37
Walk for 7 to 10 minutes to pick it up	80.63	7.83	11.55
Walk for more than 10 minutes to pick it up	86.86	5.31	7.82

Breaking these accessibility situations down by respondent group shows an even distribution of respondents who indicated frequently having to walk less than 5 minutes (Table 10). For short walk durations, the respondent groups are generally equal to or report slightly higher frequency than the overall response rate. However, for walk durations greater than 5 minutes, each respondent group reports longer walks more frequently than the overall response rate (close to twice as frequently in some instances). This result indicates there are larger proportions of these respondent groups that have lower accessibility to e-scooter services.

Table 10. Percentage of Respondents That Faced the Following Situations during the Second Pilot

Situation	All (%)	Black (%)	Low Income (%)	Priority (%)	Less Education (%)
Walk for less than 2 minutes	55.27	55.96	55.89	51.34	56.34
Walk for 2 to 5 minutes	44.35	47.71	47.01	45.59	50.91
Walk for 5 to 7 minutes	22.37	30.73	25.75	29.89	30.99
Walk for 7 to 10 minutes	11.55	21.10	15.37	16.86	19.32
Walk for more than 10 minutes	7.83	14.68	10.68	12.64	12.68

ATTITUDINAL FACTORS

Personal Experience

Respondents were also asked to rate their strength of agreement with certain statements that relate to the overall e-scooter experience (Table 11). Most respondents found using an e-scooter to be enjoyable and fun with 88.2% and 89.2% agreeing or strongly agreeing, respectively, with those statements. Many respondents also believe that e-scooters have potential in the city. Sixty-eight percent of respondents thought e-scooters made their transit more convenient, 64.8% thought e-scooters make transit more efficient, and 61.6% thought e-scooters can help solve different transportation-related issues in Chicago. Regarding the safety of e-scooters, 38.9% of respondents felt safe while 56.3% were in the middle of somewhat agreeing and somewhat disagreeing. Very few, however, felt it was unsafe. Overall, respondents tended to report that e-scooters are easy to use.

Nearly three-quarters felt the smartphone apps were easy to use, 63.4% said that e-scooters do not require a lot of mental effort, and 69.4% felt that e-scooters do not require a lot of physical effort. Respondents, however, felt a little mixed about the accessibility and effectiveness of customer service of the shared e-scooter companies, with 62.3% falling between somewhat agree and somewhat disagree.

Table 11. How Respondents Rated the Overall Experience of Using E-Scooters

Statement	Strongly agree (%)	Agree (%)	Somewhat agree (%)	Neutral (%)	Somewhat disagree (%)	Disagree (%)	Strongly disagree (%)
Using shared e-scooters is enjoyable.	57.46	30.72	5.45	1.8	1.48	0.74	2.36
Using shared e-scooters is fun.	59.17	29.98	5.54	1.85	0.92	0.74	1.8
Using shared e-scooters is safe.	13.81	25.13	32.29	13.58	10.39	2.73	2.08
Shared e-scooters are only useful for traveling to recreational activities (bar, theater, etc.).	11.87	10.12	11.82	13.21	12.98	25.22	14.78
Shared e-scooters are only useful for the sake of enjoyment and having a fun time.	10.35	9.05	8.64	11.32	12.24	28.82	19.58
Using shared e-scooters makes my travel more convenient.	33.44	34.55	19.03	8.5	2.03	1.06	1.39
Using shared e-scooters makes my travel more efficient.	31.78	33.03	19.72	10.25	2.68	0.97	1.57
Shared e-scooters are useful in meeting my daily transportation needs.	22.08	19.95	17.92	19.72	6.93	8.45	4.94
Shared e-scooters have the potential to be part of solving transportation-related issues in Chicago.	33.67	27.94	20.09	11.27	2.86	1.94	2.22
The e-scooter smartphone apps are, overall, easy to use and easy to understand.	30.81	39.4	17.14	5.5	4.11	1.57	1.48
Using shared e-scooters does not require a lot of my mental effort.	25.91	37.51	17.64	6.28	7.02	3.93	1.71
Using shared e-scooters does not require a lot of my physical effort.	29.7	39.68	16.07	5.68	5.4	2.12	1.34
If I have a problem with the cellphone-applications and shared e-scooters, I can easily get the support I need from the operators to resolve the issue.	11.59	16.44	11.87	43.28	7.16	5.68	3.97

Future Usage

E-scooters seem to be seen in a positive lens by respondents (Table 12). More than 78% of respondents would like to continue using shared e-scooters in the city, and over three-quarters of respondents would recommend using shared e-scooters to others. As seen earlier, many feel that shared e-scooters have a future in Chicago’s transportation infrastructure. Around 77% of respondents think that e-scooters make traveling easier and believe they should be a part of the transportation system in Chicago.

Table 12. How Respondents Perceive Their Future Use

Statement	Strongly agree (%)	Agree (%)	Somewhat agree (%)	Neutral (%)	Somewhat disagree (%)	Disagree (%)	Strongly disagree (%)
I intend to continue using shared e-scooters in the future.	49.52	29.47	11.69	4.34	1.89	1.25	1.85
I will recommend others to use shared e-scooters.	46	30.39	12.98	5.87	1.71	1.25	1.8
I believe shared e-scooters should be a part of Chicago’s transportation system.	48.82	28.5	10.9	7.16	1.57	1.11	1.94
An e-scooter makes it easier to reach a destination and/or complete a trip.	46.28	31.09	13.58	5.31	1.57	0.83	1.34

E-Scooter Features

A main draw toward e-scooters is the ability to avoid traffic congestion (see Table 13). More than 61% of respondents believed using e-scooters helps avoid congestion, and another 47.6% believed that e-scooters are more convenient than other modes of transportation.

Because shared e-scooters are provided by independent companies, the standard of service may vary. Table 14 presents the respondents’ opinions. Around 60% of respondents believe that the companies providing the services deliver what they promise. There are many factors that may affect this. Dependability, availability, and affordability are all important factors to the users. More than half of respondents feel that e-scooters are dependable, but the majority of respondents do not agree on availability and affordability. Regarding the availability of e-scooters, 49.1% had mixed feelings (answered somewhat agree, neutral, or somewhat disagree to the question) compared to the 44.1% that reported they typically found available e-scooters when and where they wanted them. Affordability, however, had the largest number of respondents report they had mixed feelings, with around half falling between somewhat agree and somewhat disagree.

Table 13. Reasons Respondents Indicated They Chose to Use Shared E-Scooters

Statement	Strongly agree (%)	Agree (%)	Somewhat agree (%)	Neutral (%)	Somewhat disagree (%)	Disagree (%)	Strongly disagree (%)
By using shared e-scooters, I can avoid traffic congestion.	29.24	32.66	26.74	7.67	0	2.12	1.57
By using shared e-scooters, I can improve my health.	8.96	10.9	25.91	28.04	0	20.46	5.73
Riding a shared e-scooter is more convenient than other travel modes.	19.82	27.81	34.92	12.42	0	3.6	1.43

Table 14. Perceived Level of Service Provided by E-Scooter Operators

Statement	Strongly agree (%)	Agree (%)	Somewhat agree (%)	Neutral (%)	Somewhat disagree (%)	Disagree (%)	Strongly disagree (%)
I believe that shared e-scooter companies deliver what they promise to users.	19.03	41.85	20.97	12.66	2.59	1.85	1.06
I believe that there are enough e-scooter vendors in Chicago.	21.8	38.43	14.32	13.9	5.45	3.83	2.26
I believe that shared e-scooters are dependable.	16.81	40.23	24.94	10.02	4.94	1.85	1.2
I believe that shared e-scooters are usually available wherever and whenever I want.	13.26	30.81	28.59	8.96	11.59	4.71	2.08
I believe that shared e-scooters are affordable.	10.85	22.03	23.23	11.09	16.49	8.78	7.53

Technical

Respondents were also asked about their feelings on the safety and convenience of e-scooters around the city (Table 15). Many respondents feel that e-scooters did not pose an inconvenience or threat to them while walking on the sidewalk, riding bikes, or waiting at a bus stop or train station. Nearly 70% of respondents felt that, when parked on the sidewalk, e-scooters did not cause any inconveniences or danger to them, and another 72.5% felt that e-scooters did not impede their ability to access bus stops or train stations. Slightly more respondents felt that there were more e-scooters riding on the sidewalk during this trial period compared to the 2019 pilot, but 52.0% did not notice a significant difference. In order to improve the convenience of e-scooters, around 60% of respondents felt that e-scooters should be able to be parked on residential streets, as this would likely reduce the number of e-scooters parked on sidewalks.

Table 15. How Respondents Perceive the Technical Aspects of Shared E-Scooter Services

Statement	Strongly agree (%)	Agree (%)	Somewhat agree (%)	Neutral (%)	Somewhat disagree (%)	Disagree (%)	Strongly disagree (%)
The placement of e-scooters on the sidewalk has been a source of inconvenience or danger to me	2.77	3.46	7.99	9.7	10.07	37.46	28.55
Requiring e-scooters to be locked to a fixed object when parked reduce inconvenience or danger to me	17.55	22.12	11.69	14.64	6.33	15.2	12.47
The presence of e-scooters parked on sidewalks make it more difficult for me to find bike parking	2.86	3.23	6.51	22.31	8.22	32.15	24.71
The presence of e-scooters parked on sidewalks make it more difficult for me to access a bus stop or train station	1.43	1.34	3.19	13.58	7.94	39.91	32.61
I believe e-scooters should be parked in designated racks, like Divvy bikes.	7.16	7.94	13.39	16.86	10.62	23.05	20.97
I believe e-scooters should be allowed to park on residential streets.	26.65	32.24	14.23	13.63	3.74	5.54	3.97
Compared to the 2019 scooter pilot, there were more e-scooters riding on the sidewalk.	10.21	13.9	8.22	35.2	8.59	16.3	7.58

IMPROVEMENT IN FUTURE SERVICES

Since shared e-scooter programs are new in Chicago, a portion of the survey was dedicated to collecting the respondents' opinions on various ways that the service can improve in the future. Two important areas of improvement are accessibility and safety. Nearly all respondents reported that they had used a smartphone as well as a credit card to complete their e-scooter trip, and three-quarters of the respondents reported that they did not frequently wear a helmet while riding the e-scooter (Table 16). Around 60% of the respondents would like the city to integrate e-scooter payment with Ventra to make payments easier and to add dedicated e-scooter lanes on streets in Chicago to make riding on them safer for both riders and pedestrians. Because the e-scooters are still in their trial phase, the area of operation does not cover the entire city. Some, around 40%, would like if e-scooters could be used on the Lakefront trail, and 45% would like if e-scooters could be used downtown (Figure 19).

Table 16. Respondent Opinions on Possible Improvements to E-Scooter Services

Statement	No or almost never (%)	Yes, sometimes (%)	Yes, often (%)
Did the presence of e-scooters parked on sidewalks make it more difficult for you to find bike parking?	86.74	10.62	2.63
Did you complete an e-scooter trip without using smartphone?	94.78	2.73	2.49
Did you complete an e-scooter trip without using a credit or debit card?	85.08	7.53	7.39
Do you usually wear a helmet during your ride with e-scooter?	74.97	15.61	9.42

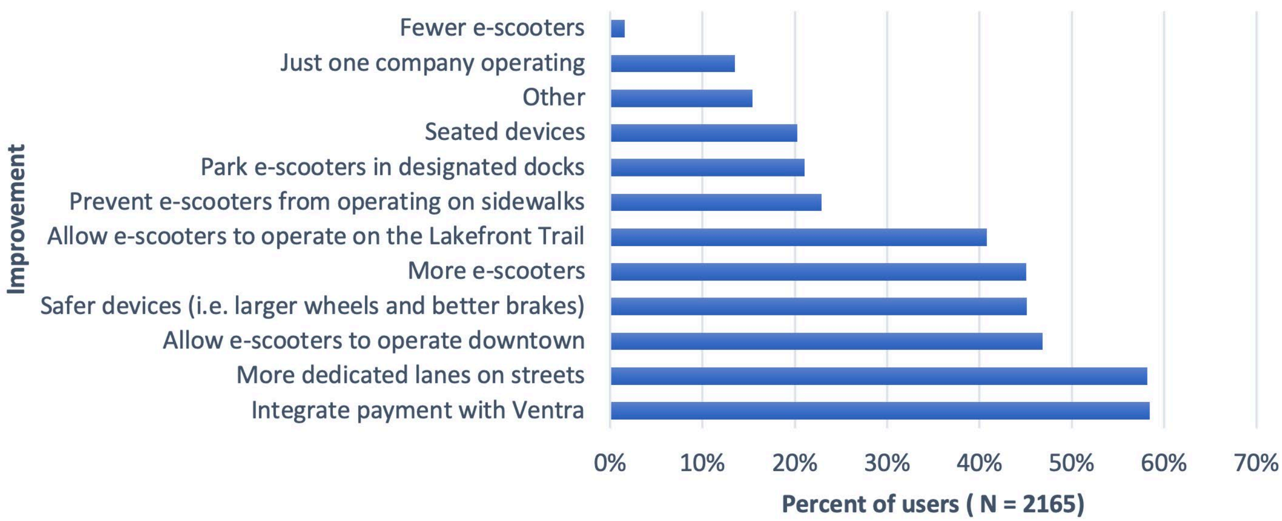

Figure 19. Bar plot. How respondents think the shared e-scooter program can be improved.

RESPONDENT DISTRIBUTION

In the survey, the researchers asked respondents to specify their home locations approximately, and researchers scattered the locations on Chicago’s network. As seen in Figure 20, most users reside in the northern part of the pilot program.

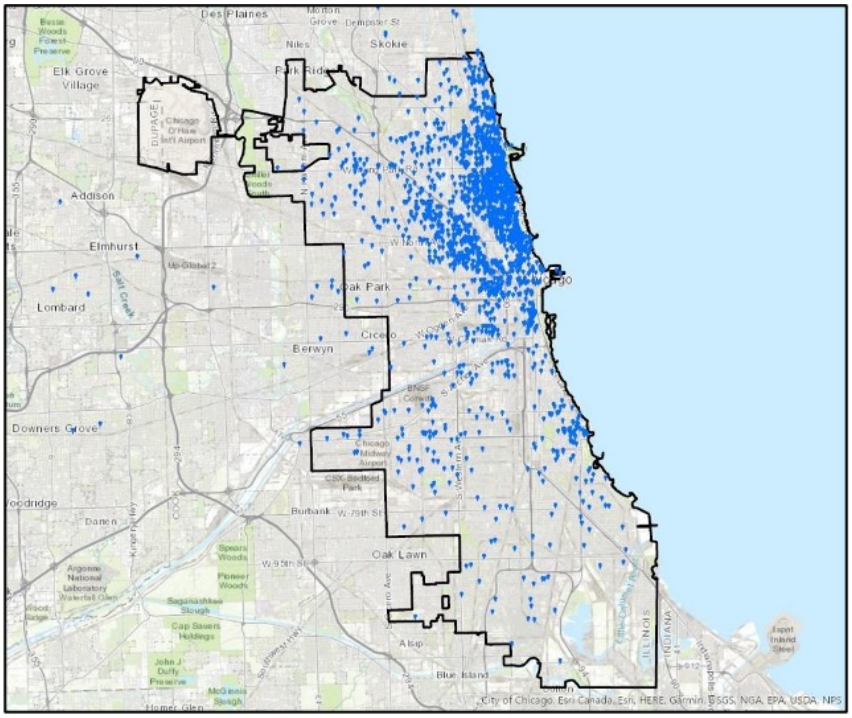

Figure 20. Map. Where survey respondents live in Chicago.

CHAPTER 4: SHARED E-SCOOTER USAGE FREQUENCY

INTRODUCTION

Promoting micromobility options in cities presents a key opportunity to reduce car-based trips and support multimodal, sustainable, and more physically active modes of transportation. Empirical evidence shows that most car-based trips in the United States are short enough that people can perform them using micromobility options if the barriers to switching from a transportation mode as comfortable as private cars are resolved (Zarif et al., 2019). According to the 2017 National Household Travel Survey, 20% of all driving trips are 1 mile or less, 33% are 2 miles or less, and 43% are 3 miles or less (U.S. Department of Transportation, 2017). Not only does this point to the role that micromobility options—such as e-scooters and e-bikes—can play in curbing the usage of cars, but also the significant health implications that such modal shifts can have from sedentary vehicle-based trips to more active modes of transportation. As a practical way to encourage people to undergo modal shifts from private vehicles, the literature suggests the integration of various micromobility options, such as docked bike-sharing programs (e.g., Divvy bikes in the city of Chicago) or dockless bike and e-scooters into cities (Fu & Farber, 2017; Gu et al., 2019; Li et al., 2019).

Nonmotorized transportation—such as walking or biking to destinations—can play an important role in promoting more physically active and positive public health outcomes. While walking and biking—as the two most active micromobility options—provide notable physical health benefits, their modal share remains low. Sixty percent of all trips that are 1 mile or less are driven, while 35% of those trips are walked, and only 2.25% of those trips are biked (U.S. Department of Transportation, 2017). As a new form of micromobility service, the shared electric scooter (e-scooter) can enhance the suite of options available in cities to promote nonmotorized transportation and fill in the gaps when walking or biking are not preferred. For example, a study conducted in Tempe, Arizona, showed that the overwhelming reason that e-scooters were used by university staff was because it was more convenient and easier than walking in the heat (Sanders et al., 2020). The addition of e-scooters to cities may help to create environments that are more conducive to cycling and walking, as cities that accommodate e-scooters have also improved their infrastructures (Schmitt, 2019). Some e-scooter companies have touted the health benefits of e-scooters as offering low-intensity workouts that can help with core strength and serve as a medium to gain further physical activity ("Pure Electric"). While more direct links between e-scooters and physical health have yet to be determined, the potential e-scooters hold to encourage travel through non-sedentary motorized transportation and cities to invest more in active transportation-friendly infrastructures may be instrumental to leading to more physically active lifestyles.

Furthermore, shared e-scooters couple the versatility of performing short- to medium-distance trips with the flexibility of not being docked at particular locations. Unlike docked shared bikes and other micromobility options, the shared e-scooter system has given its riders flexible pick-up and drop-off locations. Although e-scooters show potential as a mode of transportation, it is not clear yet whether individuals will adopt them for everyday use, especially in the COVID-19 pandemic era.

The COVID-19 pandemic has been perhaps the most significant disruption incident in modern human history, and it forced people to modify their habits to adjust to the pandemic (Salon et al., 2021; Shamshiripour et al., 2020a). More importantly, the pandemic overlapped with the widespread availability of new micromobility options in Chicago such as the shared e-scooter system. Early evidence in the United States shows that biking and walking increased during the COVID-19 pandemic (Shamshiripour et al., 2020b), which positively affects public health and transport sustainability. According to a new panel survey recently conducted in the United States, 30% of U.S. residents plan to take walks more frequently than they did before the pandemic, and nearly 15% plan to bike more in the post-pandemic era (Chauhan et al., 2021; Salon et al., 2021). To support these pandemic-induced modal shifts toward active mobility, it is imperative to characterize the influential factors affecting the usage frequency of active transport modes. While walking and biking are the two popular non-auto modes of transport studied in the literature, the role of shared e-scooters has been overlooked as a newer form of micromobility that can enhance the micromobility options that cities can offer.

This chapter aims to analyze the usage frequency of shared e-scooters in Chicago during the COVID-19 pandemic. To do so, the research team designed a survey to understand the characteristics of shared e-scooter users in Chicago and the benefits of promoting shared e-scooters in the region. This online survey launched in the Chicago region from October to December 2020 and collected a rich set of data regarding the residents' sociodemographic details and usage behavior regarding the shared e-scooter system. Consistent with the scope of this study, one question was designed to inquire about individuals' usage frequency associated with shared e-scooters during the COVID-19 pandemic. To characterize the usage frequency of shared e-scooters, the researchers utilized an ordered probit model that characterizes influential factors affecting the usage frequency of shared e-scooters while indirectly including the impacts of the COVID-19 pandemic.

SURVEY DESIGN AND DATA ANALYSIS

The final dataset for this model comprises 2,126 respondents after rejecting observations with either missing, invalid, or inaccurate information. Figure 22 shows the spatial distribution of respondents across the City of Chicago that the research team collected using Google Maps API, as shown in Figure 21. The e-scooter riders' data shows 60.1% of riders are male while 37.41% are female. The data suggests that more than 70% of shared e-scooter riders are less than 34 years old, indicating most e-scooter riders in Chicago are Millennials and Gen Zers. Regarding education, around 75% of shared e-scooter riders in Chicago have at least a bachelor's degree. Moreover, more than 90% of shared e-scooter riders have indicated that they have a driver's license. Table 17 presents summary statistics of shared e-scooter riders' key demographic attributes in the collected sample.

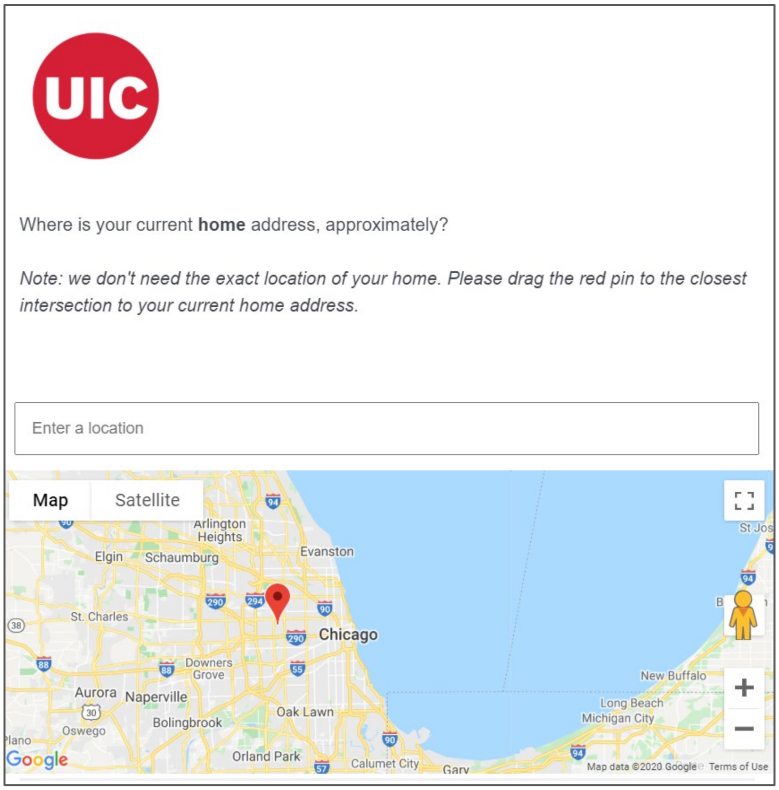

Figure 21. Screenshot. Online survey (using Google Maps API to specify residential location).

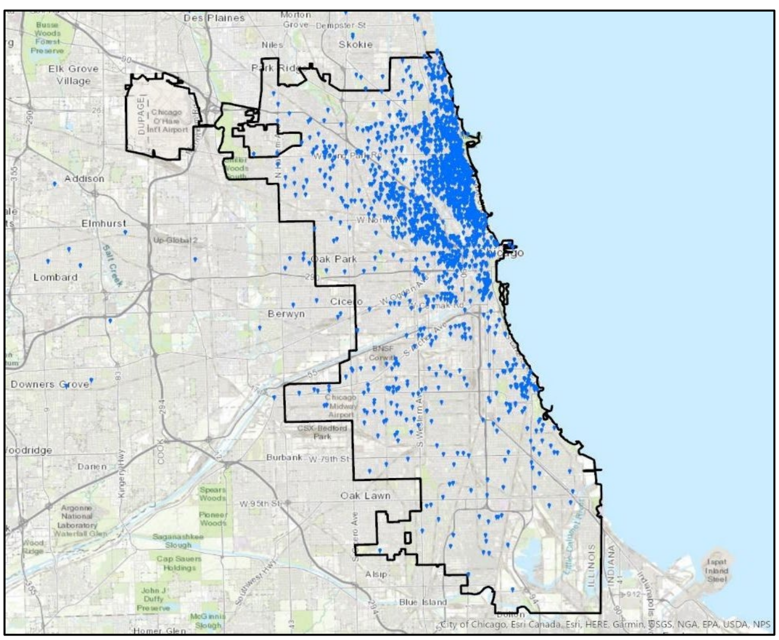

Figure 22. Map. Where the survey respondents live in the City of Chicago.

Table 17. Summary Statistics of Shared E-Scooter Users' Key Characteristics (N = 2,126)

Variable	Category	Share (%)
Vehicle ownership	0	30.80
	1	44.57
	2	18.47
	3 or more	6.14
Household income	Under $20K	9.00
	$20K–$50K	17.64
	$50K–$100K	33.07
	$100K–$150K	15.05
	$150K or more	17.18
	Prefer not to answer	8.03
Gender	Male	60.10
	Female	37.41
	Other	0.92
	Prefer not to answer	1.57
Age	18–24	17.85
	25–34	53.50
	35–44	20.28
	45–54	6.30
	55–64	1.77
	65 or more	0.28
Race	White, not Hispanic or Latino	58.90
	Black or African American	11.10
	Hispanic/Latino	16.17
	Asian	8.0
	Hawaiian or Pacific Island	0.80
	Native American	0.75
	Other	3.55
Education	High school or less	5.49
	Some college or Associate degree	19.12
	Bachelor's degree	50.02
	Graduate degree	23.69
	Prefer not to answer	1.66
Have a driver's license	No	9.7
	Yes	90.3

Note: The sum of the percentages may not equal 100 due to observations with missing values.

In this chapter, the dependent variable is derived from a question focusing on the frequency of riding shared e-scooters in Chicago. More specifically, the research team asked respondents to indicate how frequently they used shared e-scooters in the past month. Figure 23 shows the distribution of responses in the sample. According to this figure, most shared e-scooter riders indicated they took zero to three trips, including 17.1% of riders who took only one trip. More than 6% of riders said they took more than 10 trips in the last month, and the figure indicates that this relatively small group of riders took more than one-third of all trips (City of Chicago, 2021). Table 18 also defines explanatory variables that turned out to be significant in the final model.

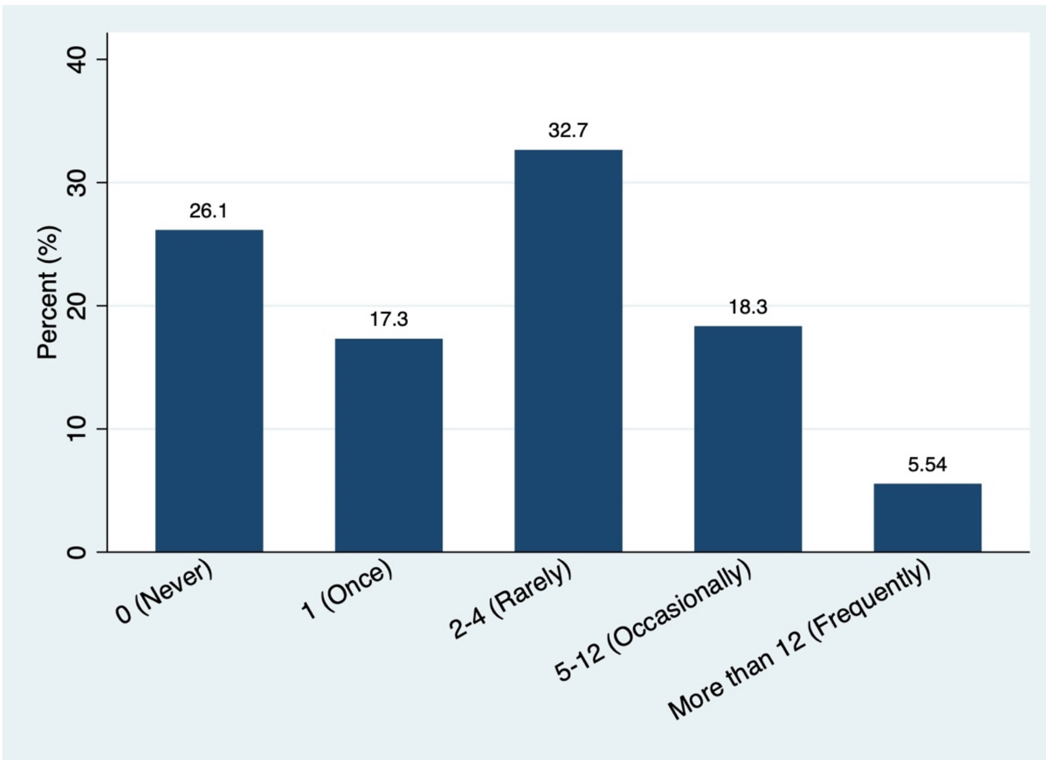

Figure 23. Bar chart. Frequency of using a shared e-scooter in the past month (between Oct.–Nov. 2020).

Table 18. Definition of Explanatory Variables Turned Out to Be Significant in the Model (N = 2,126)

Explanatory variable	Definition	Mean	Std. Dev.	Frequency (%)
Sociodemographic: White	1: If the respondent's ethnicity is White/ 0: Otherwise			69.65
Sociodemographic: LowIncome	1: If the respondent is less than $50K/ 0: Otherwise			26.65
Sociodemographic: Female	1: If the respondent's gender is female/ 0: Otherwise			37.41
Sociodemographic: Senior	1: If the respondent's age is 64 years old or more/ 0: Otherwise			0.28
Sociodemographic: GenZ	1: If the respondent's age is between 18 and 23 years old / 0: Otherwise			17.85
Sociodemographic: Millennials	1: If the respondent's age is between 24 and 34 years old / 0: Otherwise			53.50
Sociodemographic: Vehicle0	1: If the respondent's household has no personal vehicle/ 0: Otherwise			30.80
Sociodemographic: Vehicle1	1: If the respondent's household has only one personal vehicle/ 0: Otherwise			44.57
Sociodemographic: Dlicense	1: If the respondent has a driver license / 0: Otherwise			90.25
Sociodemographic: Student	1: If the respondent is a student / 0: Otherwise			16.90
Travel Behavior: ReducedFeeTransit	1: If the respondent has a discounted-rate transit card / 0: Otherwise			9.10
Travel Behavior: OnlineShopper	1: If the respondent has more than 10 incidents of online shopping in the past month / 0: Otherwise			19.58
Travel Behavior: DIVVY	1: If the respondent has bike-share membership / 0: Otherwise			22.72
Built environment: SLD_D3amm_M6	1: If network density in terms of facility miles of multi-modal links per square mile is more than 6 / 0: Otherwise			28.49
Built environment: SLD _D4c_L50	Aggregate frequency of transit service within 0.25 miles of CBG boundary per hour during evening peak period if this value is less than 50/ 0: Otherwise	0.82	5.44	
Built environment: SLD _D4dei_M3	1: If Regional Centrality Index – Transit is more than 3 / 0: Otherwise			70.71

METHOD

Because the dependent variables in this study are ordinal, the researchers utilized an ordered probit model to characterize the factors affecting usage frequency of shared e-scooters. An ordered probit structure assumes a normal distribution for error terms and prevents the estimation difficulties related to the logit structure; thus, an ordered probit model is more utilized than an ordered logit model in the literature (Washington et al., 2010).

The order probit is an underlying random utility model or latent regression model, in which the probabilities of ordinal outcomes in the model are driven by considering a continuous latent utility, y^*(Greene, 2003; Greene & Hensher, 2010; Washington et al., 2010). This variable is typically specified as a linear function for each observation (Greene, 2003; Washington et al., 2010), as in Equation (1) where, $\mathbf{X}$ is a vector of explanatory variables, $\boldsymbol{\beta}'$ is a vector of parameters to be estimated, and $\varepsilon \sim N(0,1)$ is the error term which is normally distributed across observations.

$$y^* = \mathbf{X}\boldsymbol{\beta}' + \varepsilon \qquad \text{Equation (1)}$$

The outcome variable (y) that is observed in discrete form through a censoring structure as in Eq. (2) (Greene, 2003; Greene & Hensher, 2010; Washington et al., 2010), where $\mu_1, \ldots, \mu_{J-1}$ are threshold parameters which are estimated jointly with $\boldsymbol{\beta}'$(Equation [2]). In this study, the categories of shared e-scooter usage frequency (shown in Figure 3) are assumed as 0: zero trip, 1: one trip, 2: two to four trips, 3: five to twelve trips, and 4: more than twelve trips.

$$\begin{aligned}
&y = 0 \quad if \quad y^* \leq 0 \\
&y = 1 \quad if \quad 0 \leq y^* \leq \mu_1 \\
&y = 2 \quad if \quad \mu_1 \leq y^* \leq \mu_2 \\
&\cdots \\
&y = J \quad if \quad \mu_{J-1} \leq y^*
\end{aligned} \qquad \text{Equation (2)}$$

The observed variable (y) corresponds to an integer ordering, and J is the highest ordered integer. Assuming $\varepsilon \sim N(0, 1)$, the estimation problem is to determine the probability of J for each observation (Greene, 2003; Washington et al., 2010), as shown in Equation (3). Where $\Phi(.)$ is the standard normal cumulative density function.

$$\begin{aligned}
&P(y = 0|\mathbf{X}) = \Phi(-\mathbf{X}\boldsymbol{\beta}') \\
&P(y = 1|\mathbf{X}) = \Phi(\mu_1 - \mathbf{X}\boldsymbol{\beta}') - \Phi(-\mathbf{X}\boldsymbol{\beta}') \\
&P(y = 2|\mathbf{X}) = \Phi(\mu_2 - \mathbf{X}\boldsymbol{\beta}') - \Phi(\mu_1 - \mathbf{X}\boldsymbol{\beta}') \\
&\cdots \\
&P(y = i|\mathbf{X}) = \Phi(\mu_i - \mathbf{X}\boldsymbol{\beta}') - \Phi(\mu_{i-1} - \mathbf{X}\boldsymbol{\beta}') \\
&\cdots \\
&P(y = J|\mathbf{X}) = 1 - \Phi(\mu_{J-1} - \mathbf{X}\boldsymbol{\beta}').
\end{aligned} \qquad \text{Equation (3)}$$

Having the choice probabilities from Equation (3), the log-likelihood function is given in Equation (4) (Washington et al., 2010). Where, $\delta_{in} = 1$ if the observed ordinal outcome for observation n is i; otherwise, it would be equal to 0.

$$LL = \sum_{n=1}^{N} \sum_{i=1}^{J} \delta_{in}. Ln[\Phi(\mu_i - \mathbf{x}'_n\boldsymbol{\beta}) - \Phi(\mu_{i+1} - \mathbf{x}'_n\boldsymbol{\beta})] \qquad \text{Equation (4)}$$

The joint probability for $y_1 = J$ and $y_2 = K$ are presented in Equation (4), where $\Phi(.)$ is the standard normal cumulative density function.

RESULTS

Table 19 presents the estimation results for the ordered probit model, characterizing the usage frequency of shared e-scooters in Chicago. The results include the estimated parameters, t-statistics, and the log-likelihood values at both convergence and zero. The coefficients in the model are statistically significant within a 90 percent confidence interval.

Table 19. Estimation Result of Ordered Probit Model

Parameters	Shared E-Scooter Usage Frequency Model	
	Coefficient	t-stat
Explanatory variables		
Sociodemographic: White	0.065*	1.60
Sociodemographic: LowIncome	0.184***	3.17
Sociodemographic: Female	−0.323***	−6.57
Sociodemographic: Senior	−0.977**	−2.07
Sociodemographic: GenZ	0.181**	2.28
Sociodemographic: Millennials	0.106**	1.91
Sociodemographic: Vehicle0	0.348***	5.32
Sociodemographic: Vehicle1	0.101**	1.69
Sociodemographic: Dlicense	0.329***	−3.84
Sociodemographic: Student	−0.142**	−2.00
Travel Behavior: ReducedFeeTransit	0.226***	2.59
Travel Behavior: OnlineShopper	0.144**	2.44
Travel Behavior: DIVVY	0.090*	1.61
Built environment: SLD_D3amm_M6	0.073*	1.64
Built environment: SLD _D4c_L50	−0.008**	−1.83
Built environment: SLD _D4dei_M3	0.117**	2.09
Thresholds		
μ_1	−0.61	
μ_2	−0.122	
μ_3	0.79	
μ_4	1.72	
Model Statistics		
Number of observations	2126	
Log-likelihood at zero	−3172.66	
Log-likelihood at convergence	−2442.89	
*, **, and *** mean 90%, 95%, and 99% level of confidence, respectively.		

Sociodemographic Factors

As shown in Table 19, the model indicates that race and ethnicity might be important factors influencing the usage frequency of shared e-scooters in Chicago. Per the results, white people are more likely than other racial groups to use shared e-scooters during the COVID-19 pandemic. This finding is in line with a study by Sanders et al. (2020), who suggested the significant impact of race and ethnicity on shared e-scooter usage in Tempe, Arizona. As suggested by Sanders et al. (2020), one possible reason for this finding is that the white population has more accessibility to shared e-scooters than other segments of the population, including African American, Latino/Hispanic, and black.

Also, annual household income is found to be significant in the frequency associated with the usage of shared e-scooters. Based on the model, individuals living in low-income households (i.e., household earning less than $50K per year) are more likely to use shared e-scooters than others.

Concerning gender, the results indicate that women are less likely than males to ride with shared e-scooters during the COVID-19 pandemic. Similarly, Sanders et al. (2020) highlighted the lower usage frequency of shared e-scooters by women. One possible reason is that women are less likely to perceive e-scooters as a "very safe" mode of transport and are more worried of getting hit, hitting others, falling, or losing control (Sanders et al., 2020).

According to Table 19, the age of respondents is found to affect the usage frequency of shared e-scooters. More specifically, seniors are less likely to use this micromobility option. Several possible reasons might explain this finding. In contrast, the results suggest that Millennials and Gen Zers are more likely to use shared e-scooters in Chicago during the COVID-19 pandemic. One possible reason for this finding is that Millennials and Gen Zers are more tech-savvy than older groups (Clayton et al., 2017; Lyons et al., 2016), which leads them to be adept at finding information on new mobility and micromobility services such as e-scooters. Younger generations are also physically and mentally more open to switching to active modes such as shared e-scooters.

Moreover, the research team found that having limited access to personal vehicles in households might positively affect the usage frequency of shared e-scooters during the pandemic. According to the model presented in Table 19, individuals living in households with zero or one vehicle are more likely to use shared e-scooters more frequently than others.

The usage frequency of shared e-scooters varies by variable and indicates whether a respondent is a student. More specifically, the results show that students are less likely to use shared e-scooters frequently during the COVID-19 pandemic. One possible reason is that most schools only offer virtual classes, and then students are less likely to perform trips during the COVID-19 pandemic.

Travel Behavior Factors

Shared e-scooters have the potential to interact with both transit and bike-sharing systems in two ways: 1) complementary and 2) substitution (City of Chicago, 2021). The study's findings indirectly add to the literature that such interaction might be complementary in Chicago. Per the results, those individuals who have access to reduced-fare transit cards are more likely to use shared e-scooters more frequently. Similarly, individuals who have Divvy (the only bike-share program operating in the City of Chicago) bike-share membership are more likely to use shared e-scooters more frequently.

Another variable that turned out to be significant in the model is respondents' online shopping behaviors in the past month (of the survey). As can be seen in Table 19, frequent online shoppers are more likely to perform trips utilizing shared e-scooters than others. One possible reason is that those individuals are more familiar with technologies, especially phone applications, leading them to try shared e-scooters more frequently. Also, those individuals might care more about the environment, encouraging them to use greener and safer (with respect to COVID-19) transport options such as shared e-scooters (Nazari et al., 2019).

Built Environment Factors

The study's results show that living in a block group, where the network density in terms of facility miles of multimodal links per square mile is higher, might lead people to become more frequent users of shared e-scooters during the COVID-19 pandemic. In line with the literature highlighting the effect of the built environment on shaping individuals' modality styles (i.e., the lifestyle associated with long-term mode choice decisions) (Shamshiripour et al., 2020b), this finding might be because people living in those areas are more prone toward using active modes.

Transit-related built environment variables have also turned out to be significant in the model. More specifically, where the aggregate frequency of transit service within 0.25 miles of a block group boundary (where a respondent resides) per hour during evening peak period is lower, people are less likely to use shared e-scooters frequently. This finding is in good agreement with the research team's previous results, highlighting the potential integration (complementary or substitution) of public transit with shared e-scooters. Furthermore, living in transit-oriented areas leads people to be more inclined to substitute public transit with active transport modes such as walking and biking as a safer transport option during the COVID-19 pandemic (Bucsky, 2020).

CONCLUSIONS

This study is one of the first to evaluate the frequency and trends of e-scooter usage during the COVID-19 pandemic, providing insight into how this mode was used during a major disruption. Prior to the COVID-19 pandemic, there had already been a major health crisis due to high levels of physical inactivity and sedentary behavior (Kohl et al., 2012; Ozemek et al., 2019; Pratt et al., 2020). The World Health Organization (2020) reports that 31% of individuals 15 years or older are physically inactive, and around 3.2 million deaths per year are attributable to physically inactive lifestyles. The unique context that the onset of the pandemic has brought about—notably, social distancing—means that many previously held activities have been suspended (such as physical education or athletic programs) (Shamshiripour et al., 2020a). Thus, the importance of promoting more physically active societies and enabling that through appropriate multimodalities and infrastructures is paramount.

A prime area of opportunity lies within modal shifts from sedentary and car-based travel to more active modes of transportation. Data reported by the National Household Travel Survey shows how most short trips that are less than a mile are driven, showing the potential that micromobility and active transportation can play in promoting a modal shift (U.S. Department of Transportation, 2017). As a newer form of micromobility, shared e-scooters can enhance the micromobility options available in a city and help modal shift from cars. This study set out to analyze the frequency of shared e-scooter usage in Chicago during the pandemic, thus providing insight into how the service is being used and where disparities lie.

In collaboration with the Chicago Department of Transportation, survey data was collected from registered e-scooter users in Chicago between November 20 and December 15, 2020. The data showed that 60.1% of e-scooter riders are male, while 37.41% are female. More than 70% are less than 34 years old, and more than 90% have a driver's license. The disproportionate nature of e-scooter riders shows the importance of equitable e-scooter distribution and how there should be more efforts toward provision of e-scooters in various neighborhoods across income ranges to promote accessibility to e-scooters. This is especially important given how this study's results showed that the annual household income is significantly associated with the usage of shared e-scooters, and that low-income households are more likely to use shared e-scooters.

Furthermore, this study suggests the significance of the interconnected nature of multimodal options within cities and the importance of appropriate infrastructures supporting these modes of travel. Results showed that individuals with Divvy membership (the sole bike-share program in Chicago) and those with reduced-fare transit cards were more likely to use shared e-scooters. Furthermore, results showed that density and transit-related built environment variables are also significant to more frequent use of shared e-scooters during the pandemic. Providing supportive environments suited for micromobility and the appropriate level of multimodal infrastructures such as wider bike lanes that not only support bikes, but also e-scooters can be instrumental in promoting a more comprehensive range of people—such as women and those above the age of 34—to also shift to higher frequencies of e-scooter use. The very presence and addition of e-scooters to cities has shown to lead cities to promote environments more conducive to active transportation (such as walking and cycling) (Schmitt, 2019), suggesting that cities that implement e-scooters will also become more supportive of active transportation infrastructures, in turn supporting e-bikes or other modes that better meet the needs of older adults.

E-scooters have been shown to play a critical role in diversifying the suite of multimodal options available in cities with dense networks and promoting infrastructures more supportive of active transportation. Given the devastating consequences of sedentary and physically inactive lifestyles, e-scooters can help promote modal shifts from sedentary, vehicle-based trips. Areas of exploration for future research are to analyze the direct physical health benefits of e-scooters and determine whether they lead users to live more physically active lifestyles. Another area for exploration is the relationship between e-scooter use and other active transportation modes to gain a fuller understanding of whether e-scooters promote shifts to active transportation modes of travel and how that decreases the overall mode shift driving.

CHAPTER 5: INTEGRATING SHARED E-SCOOTERS WITH PUBLIC TRANSIT

INTRODUCTION

Dockless micromobility (e.g., shared e-scooters) is rising as a complementary mode to mass transit. Fan and Zheng (2020) showed that dockless bike programs can complement transit ridership, diminishing congestion around subway stations due to access and egress. These effects have spatial and temporal characteristics, having increased effects during commute times and in urban areas with limited transit access (Fan & Zheng, 2020); this points to micromobility as a commuter mode that can aid in the creation of a sustainable transportation system. Moreover, the performance of micromobility can be highly dependent on characteristics of the built environment, as shown in Xu et al. (2019), where they found that density of development and road intersection density have the largest positive effect on dockless bike usage patterns.

The body of work regarding the integration of micromobility with transit is built on the foundation of the previous topics of sustainable development, cooperation with regional regulating bodies, and the adoption of the mode among travelers. Ni and Chen (2020) compare dockless bike programs to taxis as a complementary feeder mode with mass transit. They found that dockless bike programs better serve communities that are more residential, with lower housing prices, and poor development of mass transit. They consider built environment effects and conclude that dedicated road space, especially in regions with a high density of signaled intersections, have a large, positive impact on dockless bike program ridership whereas areas that prohibit bike use (such as parks and trails) have a negative impact on usage (Ni & Chen, 2020). Fleet availability is a major consideration for program operators, given that vehicles need to be in the right place at the right time (such as near metro areas during peak travel times) if program operators wish to avoid consequences related to overcrowding sidewalks due to lack of parking (Guo & He, 2021; Ni & Chen, 2020).

A current challenge for e-scooter researchers to address is modeling the frequency of transit integration and accounting for characteristics of travelers and of the built environment. It is vital that operators can identify the regions and time periods that vehicles need to be redistributed (Guo & He, 2021). To address this issue, the research team utilized a 35-day measurement period from 10 shared e-scooter operators in Chicago. This study aligns with the research needs for measuring the integrated usage of shared e-scooter and public transit by exploring the impacts of the built environment, temporal characteristics, and road safety attributes. This integrated usage in different conditions was studied by using a random-parameter negative binomial modeling approach. In contrast to prior behavioral studies focused on dockless electric bikes (e-bikes) and rail transit systems, which utilized limited data and relied on single-level count models (Guo & He, 2021; Wu et al., 2019), this study introduces the random-parameter modeling framework to better account for panel effect (multi-period ridership). This study is focused on shared e-scooters as an emerging micromobility mode in the United States and its integration with all mass transit systems rather than just rail transit systems.

This chapter answers the following four questions:

1) What are the characteristics of integrated usage regarding distance and duration of shared e-scooter feeder trips?

2) Do the characteristics vary in different conditions (e.g., access versus egress or morning peak versus evening peak)?

3) How do researchers measure the feeder-related built environment?

4) What are the effects that the built environment, temporal characteristics, and road safety attributes have on shared e-scooter feeder trips?

DATA

This section discusses different sources that jointly have constructed the dataset. Regarding e-scooter trips, the research team exploited the data streams of Chicago's E-Scooter Pilot Program implemented in 2019, including 10 application programming interface (API) feeds of the following companies: Wheels, Lime, VeoRide, Jump (Uber), Bird, Lyft, Sherpa, Bolt, Spin, and Clevr Mobility. These open API feeds were designed according to the general bike-share feed specification, which provided the opportunity to access the real-time location of shared e-scooters available for rent. The extracted data included 90-second snapshots of e-scooter locations throughout the 35-day measurement period from September 7 to October 11, 2019, in which every e-scooter can be identified using a unique ID. If a user unlocks the e-scooter, the data stream for its corresponding ID would be paused until it is parked again and ready to be used by the next customer. In other words, while the e-scooter is not being used, its ID and associated location are available in 90-second snapshots, whereas if it has been rented, its ID and associated location are unavailable. This pause in the data stream can be utilized to detect a reasonable "trip." Using time and distance as two measures, the research team introduce an algorithm to identify valid trips by incorporating the following points:

- If a pause is longer than a lower threshold, it is considered a *potential* trip.
- If a pause is longer than a higher threshold, it is not considered a valid trip. This is to avoid data originated problems as well as outlier removal.
- Trips including origin and destination closer than a distance threshold are treated based on the duration of the trip.

Algorithmic Steps

- **Step 1**. **Initialization**. Define T^{trip}, T^{long}, $Dist^{critical}$, and organize the data based on the e-scooter's unique ID in ascending order.
- **Step 2. Potential trip detection**. For data points corresponding to each e-scooter's unique ID, do the following: If the time difference between two consecutive data points is more than

T^{trip}, consider that time as a potential trip with the corresponding start time as well as the origin/destination.

- **Step 3. Error detection**. For each potential trip, do the following:
  - **Step 3-1**. Put $flag^{time/dist} = flag^{Long} = flag^{Speed} = 0$.
  - **Step 3-2**. If the distance between the origin and destination of the trip is less than $Dist^{critical}$and the duration of the trip is less than 10 min., put $flag^{time/dist} = 1$.
  - **Step 3-3**. If the duration of the trip is more than T^{Long}, put $flag^{Long} = 1$.
  - **Step 3-4**. If the speed of the trip is more than 15 mph (i.e., maximum velocity of e-scooters), put $flag^{Speed} = 1$.
- **Step 4. Trip validation**. For each potential trip, check the following:

$$flag^{time/dist} + flag^{Long} + flag^{Speed} = \begin{cases} 0 & Trip\ is\ valid. \\ Otherwise, & Trip\ is\ not\ valid. \end{cases}$$

The research team considered T^{trip}, T^{long}, $Dist^{critical}$ equal to 120 seconds, 3,600 seconds, and 50 m, respectively. Please note that although the snapshot was planned to be extracted every 90 seconds, several APIs stemming from different companies required accounting for the computer program running time for an extra 20 seconds. To be on the safe side, the researchers considered the 120-second threshold as the lower threshold for detecting a trip. The researchers implemented this proposed algorithm with the raw API data and extracted 102,312 validated trips distributed over the 35-day period with a mean duration of 837 seconds.

Deriving Dependent Variables

Next, the research team geo-coded each CTA bus stop, CTA rail station, and Metra station in the shared e-scooter pilot area and generated a 50 m buffer for each station. The use of e-scooters was then measured by counting the number of valid trips with origins and/or destinations within that 50 m buffer. To calibrate the radius of the buffer, this study utilized the results of a survey conducted by the research team (Rahimi et al., 2021). This survey showed that 35.8% of respondents use an e-scooter to get to/from CTA bus stops, CTA rail stations, and Metra stations. The researchers calibrated the radius of the buffer so that the number of origins and destinations for valid trips located within the buffer matched the findings of the survey questionnaire. The researchers discovered that by using a 50 m buffer, 37% of valid trip origins and destinations are within this buffer, corresponding to the survey findings. Furthermore, the researchers removed overlapping station buffers to avoid counting trips twice.

The research team used the origin and destination locations of valid trips to differentiate access and egress for integrated usage. Origins and destinations within the 50 m buffer are considered access and egress trips for integrated usage, respectively. To do so, the researchers assumed that e-scooter users who dropped off or picked up their e-scooter within the 50 m buffer intend to use CTA bus stops, CTA rail stations, or Metra stations. This assumption was also made by Wu et al. (2019) and Guo et al. (2021). Figure 24 presents the process of extracting the integrated access and egress usage. The researchers then derived the dependent variables: (1) access integration at the morning peak (i.e., 6:00 a.m.–10:00 a.m.), (2) access integration at the evening peak (i.e., 4:00 p.m.–8:00 p.m.), (3) egress integration at the morning peak, and (4) egress integration at the evening peak.

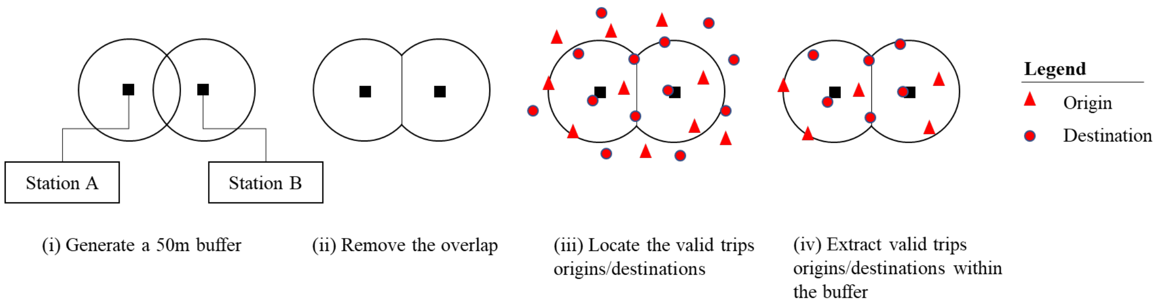

Figure 24. Graph. Identifying e-scooter and transit integration usage.

The built environment attributes (e.g., job density) of feeder trips to/from CTA bus stops, CTA rail stations, and Metra stations might have an impact on e-scooter integration, as shown in Figure 25. Because the average line distance of all valid trips is 600 m, the area within a 600 m radius of CTA bus stops, CTA rail stations, and Metra stations is the most appealing urban space, generating a large potential demand for integrated e-scooter usage. As a result, the built environment within 600 m is regarded as the contextual background. The impacts of built environment features may vary across access or egress mode and time of day. Moreover, the research team also incorporated the weather condition data into the final dataset. Figure 26 summarizes the complete data preparation process and the identification of e-scooter / transit integrated usage. Table 20 provides a statistical summary of key variables, which were found to be significant in the final models.

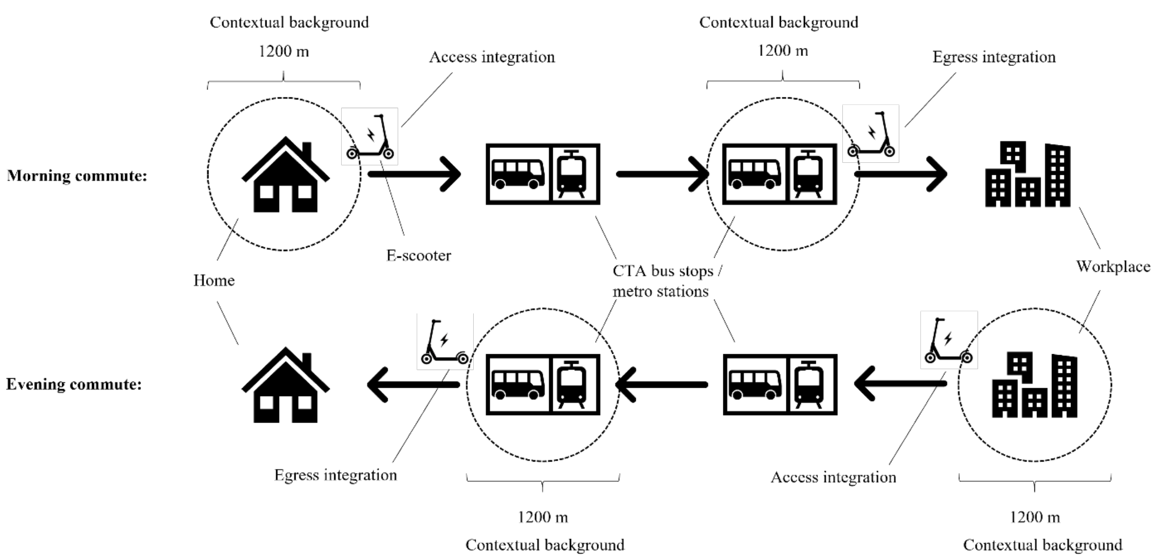

Figure 25. graph. Feeder process of connecting to CTA bus stops, CTA rail stations, or Metra stations by e-scooter.

Figure 26. Flowchart. Process of data preparation and identifying integrated usage.

Table 20. Definition of Explanatory Variables That Turned Out to Be Significant in the Model (N = 100,345)

Variables	Definition	Mean	Std. Dev.	Max	Min
Dependent					
ME	Egress integrated usage of the transit station at the morning peak within the 50 m buffer	0.08	0.97	132	0
EE	Egress integrated usage of the transit station at the evening peak within the 50 m buffer	0.105	0.62	24	0
MA	Access integrated usage of the transit station at the morning peak within the 50 m buffer	0.07	0.94	129	0
EA	Access integrated usage of the transit station at the evening peak within the 50 m buffer	0.09	0.53	23	0
Independent					
Temp_avg	Average temperature on the trip day	67.4	7.81	81	46.2
Humid_avg	Average humidity on the trip day	72.50	11.87	92.4	48.3
Pct_AO0_1	Percent of zero-car and one-car households within the 600 m buffer	0.79	0.21	1.70	0.25
E8_off10	Office jobs within an 8-tier employment[1] classification scheme within the 600 m buffer	47.07	138.28	2619.92	0
Residential_density	Gross residential density within the 600 m buffer	10.65	5.53	37.26	0.58
Activity_density	Gross activity density within the 600 m buffer	18.77	14.32	181.29	2.95
Ped_net_density	Network density in terms of facility miles of pedestrian-oriented links per square mile within the 600 m buffer	18.77	4.77	38.60	4.83
Multimodal_net_density	Network density in terms of facility miles of multi-modal links per square mile within the 600 m buffer	3.49	2.52	15.72	0
Transit_serv_freq	Aggregate frequency of transit service per square mile within the 600 m buffer	2099.65	930.38	6582.63	196.87
Transit_centrality_index	Regional Centrality Index – Transit within the 600 m buffer	0.29	0.10	0.77	0.13
Street_intersection_density	Street intersection density within the 600 m buffer	101.19	68.90	480.25	19.44
R_HiWageWk	Count of workers earning $3333/month or more within the 600 m buffer	0.31	0.14	0.75	0
Tot_accidents	Total number of accidents within the 600 m buffer	0.23	0.37	2.77	0
Tot_Crimes	Total number of crimes within the 600 m buffer	544.68	206.04	1431.93	154.05

[1] Based on Smart Location Dataset

METHOD

Because the dependent variables are count, the researchers utilized a negative binomial count modeling approach to characterize the factors affecting the integration frequency of shared e-scooter with public transit. To account for correlation among observations because data were collected over time (panel data), the researchers used a random effects version of the negative binomial count model. The following paragraphs discuss this modeling approach.

Negative binomial regression uses a Poisson-gamma mixture distribution to permit variables that are non-negative integers. The probability mass function, $P(y_n|\omega_n)$, which is given in Equation (5), is associated with the basic Poisson model,

$$P(y_n|\omega_n) = \frac{EXP(-\lambda_n|\omega_n)(\lambda_n|\omega_n)^{y_n}}{y_n!} \qquad \text{Equation (5)}$$

where, y_n is the discrete observations associated with observation n, ω_n is the random effect on observation n, and $\lambda_n|\omega_n$ is the Poisson parameter, which assumes a gamma-distributed error term for negative binomial regression and has the form given in Equation (6).

$$\lambda\_n|\omega_n = EXP(\beta_n X_n + \varepsilon_n) \qquad \text{Equation (6)}$$

β_n is an observation specific parameter vector incorporating random effect, ω_n, X_n is a vector of explanatory variables, and $EXP(\varepsilon_n)$ is the gamma-distributed error term. From this, the log-likelihood used for simulating model estimation is given in Equation (7).

$$LL = \sum_{\forall n} \ln\left(\int g(\omega_n)P(y_n|\omega_n)d\omega_n\right) \qquad \text{Equation (7)}$$

$g(\omega_n)$ is the probability density function of the random effect term, ω_n.

RESULTS

Table 21 presents the estimation results for the random-parameter negative binomial count models, characterizing the frequency of shared e-scooter trips as access or egress to public transit in Chicago. The results include the estimated parameters, t-statistics, and the log-likelihood values at both convergence and zero. The researchers assumed that the coefficients in the model are statistically significant when within a 90% confidence interval. In the Table 21, MA, EA, ME, and EE stand for morning access, evening access, morning egress and evening egress, respectively.

Table 21. Estimation Result of Random-Parameter Negative Binomial Count Models

Parameters	MA		EA		ME		EE	
	Coefficient	t-stat	Coefficient	t-stat	Coefficient	t-stat	Coefficient	t-stat
Explanatory variables								
People								
Pct_AO0_1	1.103***	6.97	0.630**	2.54	0.803**	1.90	1.539***	5.93
R_HiWageWk			−0.730**	−2.07	0.891**	1.81	0.934**	2.46
Temporal								
Temp_avg	0.065***	17.37	0.004**	1.79	0.056***	15.38	0.003**	1.81
Humid_avg	−0.024***	−9.57	−0.005***	−3.41	−0.018***	−7.56	−0.005***	−3.71
Urban space (land use)								
E8_off10	0.0009***	5.23	0.0003***	4.36	0.0009***	5.11	0.0003***	3.09
Residential_density	0.0512***	8.62	0.060***	16.43	0.092***	14.76	0.058***	14.65
Activity_density	0.004**	2.27			0.008***	3.87	0.003**	1.93
Ped_net_density					−0.044***	−5.43		
Multimodal_net_density	0.063***	5.64	0.041***	6.56			0.033***	5.01
Transit_serv_freq	0.0002***	6.96	0.0002***	9.77	0.0002***	6.86	0.0002***	11.39
Transit_centrality_index	3.78***	13.51	2.397***	7.66			2.415***	7.42
Street_intersection_density	0.003***	8.99	0.002***	11.89	0.005***	9.26	0.002***	9.13
Safety and security								
Tot_accidents					−0.285***	3.07	−0.104**	1.73
Tot_Crimes			0.0007***	4.43			0.0006***	3.80
Constant (mean)	−12.49***	−32.7	−7.05***	−18.6	−10.54***	−16.2	−8.40***	−20.9
Constant (var)	6.024		3.12		5.93		3.45	
Ln(α)	0.947		−1.007		1.279		−0.321	
Model Statistics								
Number of observations	100,345		100,345		100,345		100,345	
Log-likelihood at zero	−24815.87		−29762.046		−26876.40		−32379.39	
Log-likelihood at convergence	−15754.95		−26612.53		−17180.92		−27993.84	

*, **, and *** mean 90%, 95%, and 99% level of confidence, respectively.

People

The percentage of households with zero or one personal vehicle positively affects the integration of shared e-scooters and transit for both access and egress trips in morning and evening rush hours. Moreover, the count of workers earning $3,333/month or more (i.e., high-income workers) is positively correlated with integrated usage in ME and EE models.

Temporal

This study's findings also revealed the critical role of temporal characteristics, especially in Chicago, on the integration of shared e-scooters and public transit. According to Table 21, people are less inclined to integrate shared e-scooters with public transit when the temperature is low or humidity is high.

Urban Space (Land Use)

Many land-use variables turned out to be significant in the models. As seen in Table 21, the density of office land use adjacent to transit stations is positively associated with integrated usage in all four models. This finding is in line with a study by Guo and He (2021), in which they reported similar findings. The results of the current study also show the positive effect of residential density on integrating shared e-scooters with public transit in all four models.

This study's results found that activity density is positively correlated with the joint use of shared e-scooters and public transit in all models, excluding egress trips in morning rush hours. One possible reason is that the density of mixed land use is higher in those areas; people in those areas are more eager to use shared e-scooters as a feeder mode of public transit (Lin et al., 2018; Tu et al., 2019). The findings further revealed when and what type of feeder trips are affected by activity density.

As indicated by the literature, a bikeway is vital for using active modes because it makes riders feel comfortable and safe (Griffin & Sener, 2016; Martens, 2007). In this study, the researchers found that a higher density of multimodal links adjacent to transit stations significantly affects the integration of all access trips as well as egress trips in evening rush hours. The results showed a positive correlation between the density of intersections and the frequency of e-scooter trips as a feeder mode.

Moreover, the findings highlighted the significant effect that access to public transit has on integrating transit with shared e-scooters. Per all four models, a higher frequency of transit services within the 600 m buffer of the stations might encourage people to integrate shared e-scooters with public transit more frequently. A similar finding has also been reported by Guo and He (2021).

Safety and Security

The total number of accidents within the 600 m buffer area of transit stations is found to be significant in ME and EE models. Having access to safe roads for walking and biking might be more attractive for urban travelers who walk or bike than crowded, dangerous, and costly streets used by private vehicles (Moeinaddini et al., 2015). Thus, it is plausible that the total number of accidents, as a proxy variable for road safety, negatively affects the integration of shared e-scooters with public transit for egress trips.

According to Table 21, the total number of crimes is positively correlated with the frequency of using shared e-scooters as a feeder mode of public transit. Accordingly, one possible explanation for this study's finding is that when people feel less safe walking, they might switch to another available option, which can be shared e-scooters. The literature suggests that the higher crime rate in a neighborhood, the fewer people who walk (Shamshiripour et al., 2019). In addition, a recent survey of shared e-scooter users in Chicago revealed that people usually substitute the shared e-scooter mode with walking (City of Chicago, 2021).

CONCLUSIONS

This chapter investigated the impacts that the built environment, temporal characteristics, and road safety have on integrated usage during peak hours. To do so, the research team utilized a 35-day measurement period from 10 shared e-scooter operators in Chicago. Next, the researchers used a random-parameter negative binomial count model to measure the impacts of the built environment, temporal characteristics, and road safety attributes on the integrated usage of shared e-scooters with public transit. According to the conditions of e-scooter usage as an access or egress mode for a given time of day, the research team seperated the integrated usage into four scenarios: (1) access integration at the morning peak, (2) access integration at the evening peak, (3) egress integration at the morning peak, and (4) egress integration at the evening peak. The researchers then estimated four models for these scenarios. The finding of this study revealed the critical role of temporal characteristics, which showed that people are less inclined to integrate shared e-scooters with public transit when the temperature is low or humidity is high. The study also indicated that the total number of accidents, as a proxy variable for road safety, negatively affects the integration of shared e-scooters with public transit for egress trip and the total number of crimes is positively correlated with the frequency of using shared e-scooters as a feeder mode for public transit. Moreover, the findings highlighted the importance that the number of vehicles per household, income, and many land-use factors have on e-scooter usage patterns, as discussed in previous studies.

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