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Motivations and Mode-choice Behavior of Micromobility Users in Washington, DC

Siddartha Rayaprolu[a,*], Mohan Venigalla[a]

[a] *Sid and Reva Dewberry Department of Civil, Environmental and Infrastructure Engineering, George Mason University, Fairfax, VA 22030-4400; *Corresponding Author*

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ABSTRACT

The COVID-19 pandemic has reduced travel in general and disrupted travel patterns across the United States. The transit and ridehailing service ridership are particularly severely impacted. After an initial dip, shared micromobility services, including bikeshare, e-scooters, and e-bikeshare, have gained popularity as social distancing promoters with fewer points of contact. The findings of this article are based on the first phase of a two-phase mixed-mode survey of users and non-users of micromobility in Washington DC (n=440) in the Summer of 2019. While the phase-2 of the study is impacted by COVID-19 prevalence, results from the phase-1 are expected to serve as a critical baseline for post-pandemic travel behavior analysis and policy design. Findings indicate that each micromobility mode caters to different trip purposes and trip lengths of riders. While pleasure and time are identified as the biggest motivator for users, safety and pricing remain the most prominent barriers to users and non-users. Women and ethnic groups prefer to stay unimodal. Young and low-income users tend to be multimodal in their micromobility usage.

Keywords: Micromobility, Capital Bikeshare, E-scooters, E-bikeshare, Dockless bikeshare, Intercept survey, logistic regression, COVID-19

1. INTRODUCTION

As evidenced by their rapid adoption in recent years, shared micromobility services have resonated with consumers and investors, pointing to the likelihood of even more rapid growth in the future. Despite their widespread deployment in several metropolitan areas, very little is understood about the profiles and preferences of e-scooter users vis-à-vis a more mature station-based bikeshare system. As COVID-19 disrupted the travel behavior of users, it is of great importance to have a baseline reference to compare with the post-pandemic mode-choice behavior.

Earlier studies on station-based bikesharing have documented noteworthy findings on user demographics, mode-choice preferences, and the spatial equity of service [*1*]–[*5*]. However, very little is known about the relatively recent dockless systems users and their interactions with other modes. There are limited user-surveys that effectively portrayed the differences in characteristics among different micromobility users to understand their mode-choice behavior patterns. Furthermore, there are no past studies that analyze the multimodal behavior of micromobility users. A detailed summary of the user-survey literature is presented in Table 1

This research aims at understanding the demographics, perceptions, and preferences of micromobility users – both in absolute and relative terms - through a mixed-mode survey of micromobility users in the Washington DC metro area. We approach this goal by emphasizing three research questions:

1. What makes a person choose one micromobility mode over the other?
2. Which set of micromobility users tends to be multimodal?
3. How do users perceive individual micromobility mode?

2. THE STUDY AREA CHARACTERISTICS AND METHODOLOGY

At the time of this study (July 2019), Washington DC hosted seven e-scooter operators, one station-based bikeshare and one dockless e-bikeshare programs. The city also hosted dockless bicycles between late 2017 to early 2019, which were later replaced by e-scooters.

2.1 Survey design

A two-page mixed-mode survey instrument was designed to capture various characteristics of micromobility users. Approved by the Institutional Review Board, the survey was tailored to capture four types of potential respondents.

1. Capital Bikeshare (CaBi) users that do not prefer to use dockless vehicles
2. Users that prefer both CaBi and dockless vehicles based on individual trip purpose
3. Old CaBi users that completely shifted to dockless systems
4. New dockless vehicle users that never tried any micromobility systems before.

Dockless vehicle users include users from e-scooter, e-bikeshare and past dockless bikeshare services.

Table 1. Summary of recent literature on different shared-micromobility services

Authors	Year	Study area	Methods	Findings
				Station-based bikesharing
Kaviti et al.[3]	2019	Washington, DC	Survey	The majority of registered CaBi users (82%) chose bikes for commuting purposes, while a majority of casual CaBi users (57%) use them for social /recreational /sight-seeing /touring purposes
Chen, M., et al.[6]	2018	Hangzhou, China	Survey	1. Station-based bikesharing (SBS) and Free-floating bikesharing (FBS) have similar user structure, but different factors influence use frequency 2. SBS's strength is to have good quality with low cost while FBS is more flexible and is free to use
Buehler, R. & Hamre., A[7]	2019	Washington, DC	Survey	3. Savings in travel time (73% of users) and cost (25% of users) are significant motivators of CaBi. 4. Joining CaBi to save money had a significant positive association with new trips
				Dockless bikesharing
Hirsch et al.[8]	2019	Seattle, WA	Survey	Most resident bikeshare users are disproportionately young and white men who already use bicycles
Chen, Z., et al.[9]	2020	Beijing, China	Survey	1. Dockless bikeshare systems are more popular among younger, higher educated, or median-income groups and appear to be gender-independent. 2. Having a pro-bicycle attitude helps in the mode-choice behavior but does not account well for usage frequency
				E-bikesharing
Dill, J., & Rose, G.[10]	2012	Portland, OR	Survey	E-bikes help overcome some of the demographic barriers in society. They also address concerns over health problems related to inactivity, pollution, and other public policy problems to which private vehicles contribute
Campbell, A.A. et al.[11]	2016	Beijing, China	Survey	1. The average trip length of e-bikeshare in china to be between 2.5 to 2.8 miles. 2. They tend to divert users away from both the sheltered and unsheltered modes, as users tend to be less sensitive to trip distance, poor air quality, and severe temperatures.
He at al.[12]	2019	Salt Lake City, UT	Survey	1. The presence of e-bike systems near denser public areas with higher economic and recreational activity has a positive relationship with their ridership. 2. An average user identifies to be a visitor with a trip length of at least 5 miles, regardless of the hilly terrain.
Heineke et al.[13]	2019	United States	Market research	In the US, there is a $200B to $300B market potential for short-distance trips (under 5 miles), and shared micromobility can capture conservatively about 8 to 15% of this market
				E-scooter sharing
Smith, S.C., & Schwieterman, JP.[14]	2018	Chicago, IL	Trip data analysis	1. Popular trip length is between 0.5 to 2.0 miles. E-scooters can increase trips from 47% to 75% in a parking-constrained environment. 2. E-scooters do not compete with transit for longer trips due to economic viability, and they make at least 16% of jobs more accessible within 30 min of ride time
Liu et al.[15]	2019	Indianapolis, IN	Trip data analysis	The popular trip length of e-scooters is between 0.5 to 2.0 miles
Clewlow, R.[16]	2019	United States	Survey	1. E-scooters attained better gender equality compared to the earlier studies in the station-based bikesharing system. 2. 70% of the survey respondents supported micromobility and considered e-scooters a much convenient form of transport than personal car ownership.
James et al.[17]	2019	Arlington, VA	Survey	E-scooter trips in Rosslyn replaced trips otherwise taken by Uber, Lyft, or a taxi (39%), foot (33%), bicycle (12%), bus (7%), or car (7%)
McKenzie, G.[18][19]	2019	Washington, DC	API Data Analysis	1. The trip length of e-scooters is less than 5 min, as opposed to CaBi members (15 min) and casual users (40 min). 2. Capital Bikeshare tends to be more commuter focused whereas LimeBike reflects more leisure or non-commute related activities

Table 1. Summary of recent literature on different shared-micromobility services

Orr et al.[20]	2019	Portland, OR	Pilot/ Survey	1. Most users were people of color (74%), < 35 years (71%), with incomes < $30,000 (66%). 2. In the absence of e-scooters, people made trips with a motor vehicle (34%), TNCs/Taxis (15%), and Personal car (9%). 3. Cannibalized pedestrians (37%) and personal bike riders (5%). Attracted non-bikeshare users (74%) and non-bicyclists (42%) 4. Average trip length of 1.15 mi. Where users preferred e-scooters for trip connections (71%) and social/recreation trips (29%)
Sanders, R.L., et al. [21]	2020	Tempe, AZ	Survey	1. E-scooters used more for transport than recreation 2. Non-white non-riders significantly more likely to intend to try e-scooters 3. E-scooters disproportionately replace walking and bicycling for all trip types. 4. Women are significantly more likely to cite safety-related barriers to e-scooter use.

2.2 Survey execution

The intercept survey was conducted at 12 locations with higher activity of micromobility users. This field selection step was made based on preliminary observations from historical trip data of CaBi and E-scooters to understand the origin-destination patterns of these micromobility modes. Adequate samples were collected from all eight wards of Washington, DC, to ensure proper geographic coverage.

Although the intercept survey was designed to capture the users from the above categories of 1 and 2, it had limited potential to capture the resident respondents from categories 3 and 4. Such lack of response is a result of the time and price sensitivity of the dockless users, who does not prefer to be interrupted. Earlier research supports the importance of mixed-mode surveys in reducing the non-response error, and improve the quality of the data collected [22], [23]. Therefore, a web-version of the survey was circulated among the universities, major employer locations in the region, Reddit, Twitter, and LinkedIn.

3. DATA ANALYSIS AND RESULTS

A total of 440 responses from users and non-users of micromobility systems were analyzed. Users and non-user responses were distinguished based on an inbuilt option of "never used one before", within the questionnaire. A total of 309 respondents (Paper-based: 171; Web-based: 138) were found to have used a micromobility service at least once. Steps were taken to combine the responses from the mixed-mode survey and validate the sample against earlier peer-reviewed user survey studies on CaBi and E-scootersharing are described below.

3.1 Data validation

Table 2 presents the results of Pearson's chi-square test that compares the intercept and web-based survey samples. The test statistic, in conjunction with Cramer's V statistic, provides the strength of association between the two survey samples, in order to combine the datasets for model building. Except for gender, the respondent distribution from two types of surveys is not significantly ($\alpha = 0.05$) different from each other. Goodness-of-fit evaluations of current CaBi users against past user-survey study [24] indicate that the current sample of casual users closely resembles the CaBi users in all aspects except gender (Table 3). E-scooter users from the current survey were compared to the sample distribution of Portland's e-scooter pilot study (Figure 1). The percentage distribution of gender and racial characteristics of the users between the two studies are similar. However, the income group classifications among low-income groups appear dissimilar. Both studies suggest a higher dominance of higher-income groups among users.

Table 2. Pearson's Chi-square test for goodness of fit: intercept vs web-based surveys

Category	Subcategory [a]	Survey method: Intercept (n=171)	Survey method: Web *(n=138)*	χ^2	df	p-value	Cramer's V	Inference (based on α = 0.05)
Age	21-29 yrs.	73	73	5.681	3	**0.128**	0.126	*The age of the respondent is independent of the type of survey. Causation can be drawn on aggregated data*
	30-39 yrs.	64	48					
	40-49 yrs.	19	9					
	50-59 yrs.	13	5					
Gender	Female	68	38	4.312	1	0.038	0.137	*There is a moderate relationship between the gender of the respondent and the type of survey.*
	Male	101	97					
Income	< $20k	25	16	11.353	6	**0.078**	0.193	*The income group of the respondent is independent of the type of survey. Causation can be drawn on aggregated data*
	$20k-$34k	11	6					
	$35k-$49k	14	8					
	$50k-$74k	36	17					
	$75k-$99k	34	32					
	$100k-$149k	32	29					
	>$150k	17	28					
Race / Ethnicity	Asian	6	14	8.196	4	**0.085**	0.165	*The race/ethnicity of the respondent is independent of the type of survey. Causation can be drawn on aggregated data*
	Black/African American	9	10					
	Hispanic/Latino/Spanish origin	19	12					
	White	126	85					
	Other	10	11					

[a] *Subcategories with a sample size of fewer than 5 respondents were not included in the test due to the chi-square test's analytical limitations.*

Table 3. Sample characteristics of the current survey compared to CaBi user survey in 2017

The goodness of fit tests: Validation of the sample distribution

	Capital Bikeshare Members					*Capital Bikeshare Casual users*				
	2017[a]	2019[b]	χ^2	df	p-value[c]	2017	2019	χ^2	df	p-value[c]
	(n = 317)	(n = 86)	Inference			(n = 305)	(n = 148)	Inference		
Gender			1.2309	1	0.267			9.3684	1	0.002
Male	212	52	The gender composition of the two samples is not different			162	98	The gender distribution of casual users from both samples are different		
Female	105	34				155	50			
Ethnicity			1.379	1	0.2404			2.5604	1	0.1096
Non-White	60	22	The ethnic composition of member respondents is not different			103	43	The ethnic composition of casual users from both the surveys may not be different		
White	244	58				179	105			
Income			4.5174	2	0.1045			2.1234	2	0.3459
Low: < $35,000	32	10	The income level of the member respondents from both the surveys is not different			76	33	The two samples are different		
Medium: $35,000 - $100,000	127	44				130	70			
High: > $100,000	159	32				111	43			

[a] Capital Bikeshare user survey data from 2017, conducted by Shruthi et al. (Kaviti, Venigalla, and Lucas, 2019)

[c] The corresponding p-values were computed through the Monte Carlo simulation of B-replicates. Thereby, the degrees of freedom of the approximate chi-squared distribution of the test statistic are "NA"

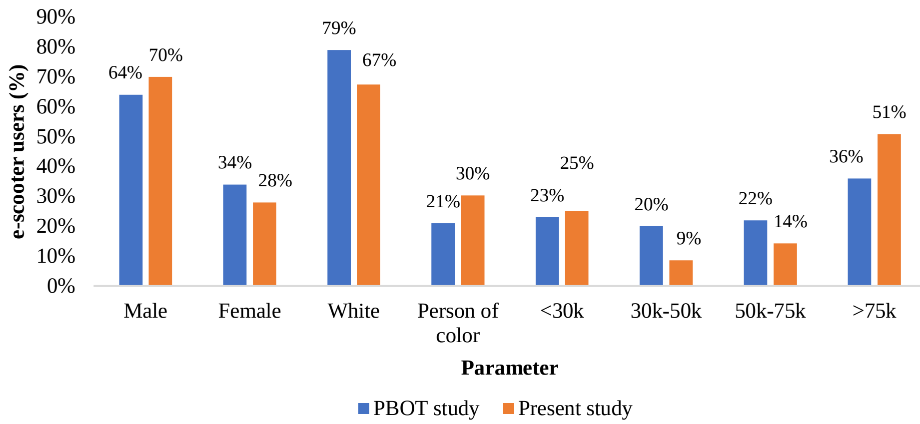

Figure 1. User characteristics of the current study v. Portland's pilot study

3.2 Logistic regression and odds ratio

The demographic characteristics of micromobility users (Figure 2) indicate perceivable differences between the users of multiple micromobility modes. Two logistic regression models (Table 4) were developed: One–to estimate the log-odds of the multimodal behavior of all the micromobility users; Two–to estimate the log-odds of the micromobility mode-choice outcomes of bikeshare users (CaBi and E-bikes) in comparison to E-scooter users. The logistic regression method estimates the odds or probability of response variable to take a particular value in response to a critical predictor value, usually while holding other predictors constant [25]–[27].

Multimodality refers to the tendency of a user to ride multiple transportation modes to reach their destination. The first regression model analyses the log-odds probability of a user to ride a single or multiple micromobility modes among all the four choices. Users that prefer to ride a single micromobility mode are classified as 'unimodal,' and the others are classified as 'multimodal'. The second model estimates the relative mode-choice preferences of bikeshare and e-scooters. Inferences from both the models together indicate the extent, serviceability and influence of each micromobility mode on a particular group of users.

The explanatory demographic variables include gender, age, income groups, ethnicity, car ownership, and usage frequency. The 'frequency of usage' variable is classified into two categories: Occasional (<1 ride per week) and Frequent (1 or more rides per week). Results from the Logistic regression of multimodal behavior of among micromobility users indicate that women (p-value=0.018) and people of color (p-value=0.052) are more likely to be unimodal, at higher significance levels. Lower-income groups (p-value=0.034) and younger users (p-value=0.032) are more likely to be multimodal. The comparative model indicates that younger users are more likely to choose e-scooters over CaBi (p-value=0.007) and E-bikeshare (0.036). Females (p-value=0.039) and medium-income households (p-value=0.053) are more likely to choose CaBi over e-scooters. There is no evidence of the significant influence of race, and personal car usage on the relative mode-choice.

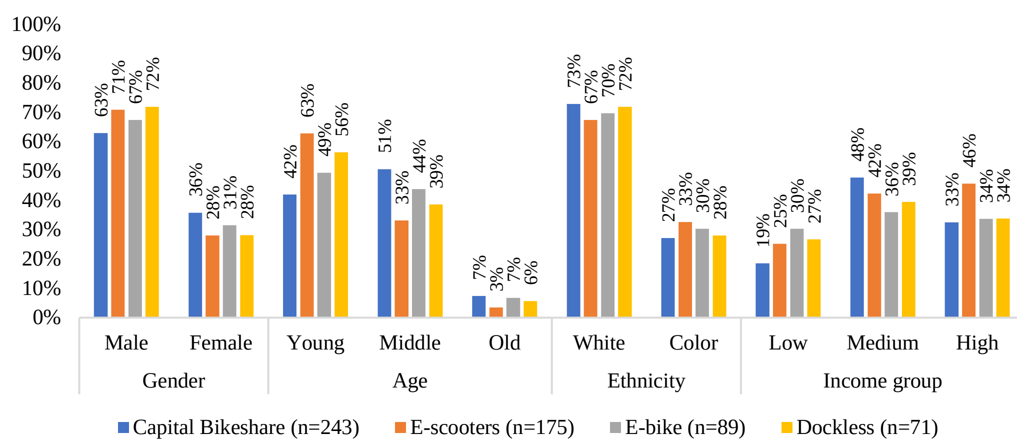

Figure 2. Demographic characteristics of micromobility users in Washington, DC

Table 4. Logistic regression models on user characteristics and mode-choice behavior

Logistic regression model 1: Multimodal characteristics of micromobility users								
Mode (marginal %)	**Parameter (marginal %)**		**β**	**SE**	**p-value**	**Exp(B)**	**95% CI**	
		Intercept	-1.084	0.525	**0.039**		**Lower**	**Upper**
Multimodal User (45.2%)	Gender	Female (34.9%)	-0.623	0.263	**0.018**	0.536	0.321	0.897
	Age	Young (48.3%)	1.245	0.581	**0.032**	3.474	1.112	10.852
		Middle (44.5%)	0.986	0.558	0.07	2.679	0.898	7.993
	Income	Low (18.8%)	0.878	0.414	**0.034**	2.405	1.069	5.409
		Medium (47.3%)	0.107	0.295	0.716	1.113	0.624	1.985
	Race	Non-White (30.5%)	-0.53	0.272	**0.052**	0.589	0.345	1.004
Model fitting criteria	**(-2) Log-Likelihood**		**Chi-square**		**df**		**Sig.**	
	90.149		21.849		6		0.001	
Pearson's goodness-of-fit statistics			33.058		23		0.08	
a. The reference category is Unimodal user								
Reference parameters: Male, Old, High income, and White users of micromobility								

Logistic regression model 2: Mode-choice preferences of bikeshare users in reference to e-scooter users								
Mode (marginal %)	**Parameter (marginal %)**		**β**	**SE**	**p-value**	**Exp(B)**	**95% CI**	
		Intercept	1.656	0.61	0.007		**Lower**	**Upper**
Capital Bikeshare (48%)	Gender	Female (33.1%)	0.481	0.233	**0.039**	1.618	1.025	2.555
	Age	Young (51.6%)	-1.593	0.589	**0.007**	0.203	0.064	0.645
		Middle (44.9%)	-0.607	0.555	0.274	0.545	0.184	1.617
	Income	Low (22.9%)	0.577	0.367	0.116	1.781	0.867	3.659
		Medium (44.9%)	0.54	0.279	**0.051**	1.716	0.99	2.967
	Race	Non-White (28.3%)	-0.208	0.24	0.386	0.812	0.508	1.3
	Car ownership	No (40.7%)	-0.024	-0.379	0.949	0.976	0.465	2.05
		Yes (48.2%)	-0.094	0.361	0.794	0.91	0.448	1.847
	Usage	Occasional (68.4%)	-0.945	0.242	**0.000**	0.389	0.242	0.625
		Intercept	-0.44	0.775	0.57			
E-bikeshare (17.5%)	Gender	Female (33.1%)	0.306	0.297	0.304	1.357	0.758	2.431
	Age	Young (51.6%)	-1.537	0.733	**0.036**	0.215	0.051	0.905
		Middle (44.9%)	-0.494	0.681	0.468	0.61	0.161	2.317
	Income	Low (22.9%)	0.701	0.454	0.123	2.015	0.828	4.907
		Medium (44.9%)	0.012	0.361	0.97	1.012	0.499	2.056
	Race	Non-White (28.3%)	-0.158	0.304	0.603	0.854	0.47	1.55
	Car ownership	No (40.7%)	0.386	0.49	0.43	1.472	0.564	3.841
		Yes (48.2%)	-0.138	0.467	0.767	0.871	0.349	2.174
	Usage	Occasional (68.4%)	0.594	0.369	0.108	1.81	0.879	3.73
Model fitting criteria	**(-2) Log-Likelihood**		**Chi-square**		**df**		**Sig.**	
	332.91		65.899		18		0	
Pearson's goodness-of-fit statistics			110.974		192		1	
a. The reference category is E-scooters								
Reference parameters: Male, Old, High income, White, Car owners that do not drive, and Frequent users of micromobility								

3.3 Shared and Micromobility Mode-choice and Trip length

A chi-square test of independence among the user preferences of CaBi, e-bikeshare, and e-scooter indicated that the mode-choice is predominantly dependent on trip purpose ($\chi 2$: 14.31, p-value: 0.02636). Figure 3 illustrates the mode-choice preferences of the private shared-mobility and micromobility modes through a stacked bar plot.

Average trip length is useful in understanding the role of a particular mode within a set of modes available to a user. It depends on several factors like time and price sensitivity of the customers and trip purpose. The odds ratio analysis (Table 5) suggests that e-bikeshare and CaBi are more popular for trips less than 5-min and trips between 15-30 min, respectively. While E-scooters are found to be popular for 5-15 min trips, this finding is less significant.

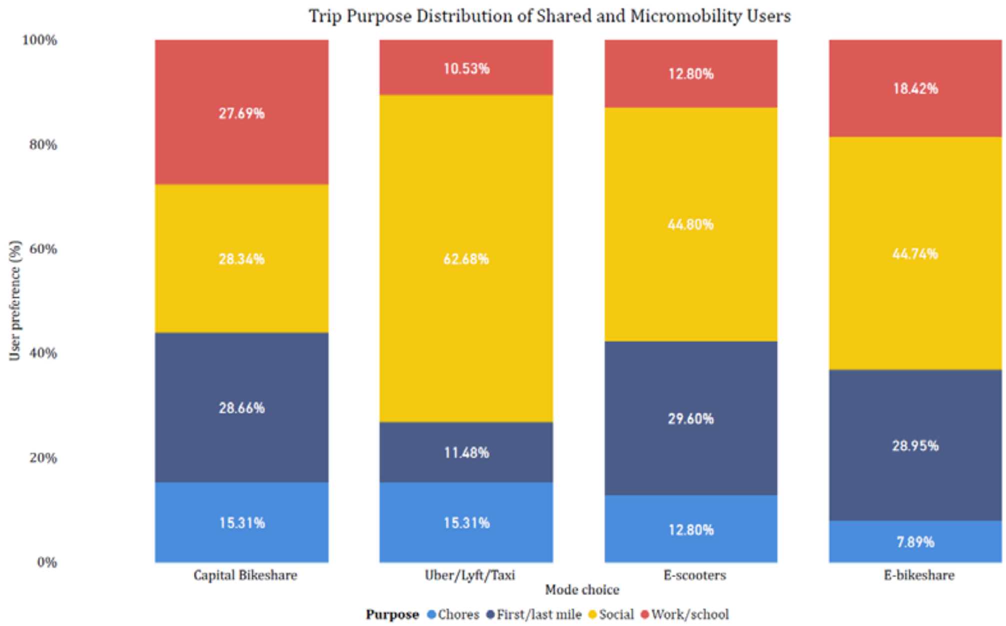

Figure 3 Mode-choice of micromobility users based on trip purpose

Table 5 Trip-length based odds ratio analysis of mode-choice

Trip length	Reference Service	Parameter	*Capital Bikeshare	Dockless bikeshare	E-bikeshare	Scootershare
			(n = 237)	*(n = 71)*	*(n = 77)*	*(n = 160)*
< 5 min	E-bikeshare	Odds ratio	4.34	0.783		1.6
		95% Conf. interval	2.212 < OR < 8.515	0.39 < OR < 1.573		0.8538 < OR < 2.998
5 - 15 min	Electric scooters	Odds ratio	1.191	1.418	1.239	
		95% Conf. interval	0.798 < OR < 2.615	0.7946 < OR < 2.531	0.7143 < OR < 2.149	
15 - 30 min	Capital Bikeshare	Odds ratio		2.062	1.913	2.514
		95% Conf. interval		1.166 < OR < 3.647	1.108 < OR < 3.301	1.624 < OR < 3.892

** Third generation bikeshare;*

Interpretation examples:

[1] The odds of choosing Dockless bikeshare for trips < 5 minutes are 5.5 times higher than that of Capital Bikeshare

[2] The odds of choosing Capital Bikeshare for trips 15-30-minute duration are 2.237 times higher than that of Dockless bikeshare

3.4 Shared and Micromobility Mode-choice and Trip length

Very little is known about the reasons behind the relative differences in consumer affinity for these shared micromobility systems. Users and non-users were asked to provide their opinion on potential reasons for using different modes 'more' or 'less' often. While users perceived these modes as fun and time-saving alternatives, safety and disinterest remain major barriers to their patronage among both users and non-users Figure 4. Among all micromobility modes, e-scooters were significantly considered to be unsafe.

Around 23% of the respondents considered e-scooters unsafe, but a majority of them considered them to be fun (59%) and time-saving (51%). This observation complements our earlier finding that e-scooters are more preferred for social and recreational trip purposes. Among all micromobility modes, both e-scooters and CaBi provide better-perceived incentives to the users than the other two modes included in the survey. However, CaBi appears to have added advantages of being perceived as more economical, fitness-promoting, time-saving, and easier to use than e-scooters.

Anecdotal references from the survey respondents indicate that most CaBi users prefer not to use other modes due to their existing long-term membership. However, some users expressed their interest in using the e-scooters for social or recreational purposes occasionally. This observation reinforces our earlier deductions from the odds ratio analysis that CaBi members are more likely to use e-scooters occasionally than regularly. Furthermore, several respondents indicated that the uncertainty in the dockless vehicles' availability at a specific location had reduced their interest in choosing those modes.

Question: What makes you ride this micromobility mode more often?				
Incentives	Capital Bikeshare (n=244)	Dockless Bikeshare (n=71)	E-bikeshare (n=89)	E-scooters (n=175)
Hassle free/ Easy to use	45%	25%	27%	39%
Economical	48%	21%	16%	23%
Time saving	45%	27%	39%	51%
Safe	11%	7%	6%	4%
Healthy	45%	20%	10%	7%
It's fun!	47%	30%	39%	59%
*Question: What makes you ride this micromobility mode less often?**				
Barriers	Capital Bikeshare (n=440)	Dockless Bikeshare (n=440)	E-bikeshare (n=440)	E-scooters (n=440)
Not interested/ Not viable	36%	45%	44%	34%
Expensive	8%	13%	16%	18%
Time consuming	5%	2%	2%	2%
Unsafe	10%	8%	9%	23%
Traffic/Pollution	6%	4%	4%	7%
Scale				
Most preferable			*Least preferable*	
100%	80%	60%	40%	20%
**Both users and non-users were asked to provide their opinion*				

Figure 4 Heat chart of the user and non-user perceptions on individual micromobility mode

4. DISCUSSION AND CONCLUSION

Logistic regression results suggest that lower-income groups and younger adults are more likely to ride multiple micromobility modes. As each micromobility mode caters to different trip purposes and trip lengths, multimodality indicates the consistency of user reliability on micromobility modes for most of their travel needs, without drifting away to high-carbon modes. For example, survey responses suggest that e-scooters attracted users from personal cars (36%) and Uber/Lyft/taxi services (22%). While younger adults have a higher likelihood of using e-scooters, women and medium-income groups preferred CaBi to e-scooters. Significant differences in trip lengths and trip purposes among different micromobility users indicate that each mode caters to the needs of specific groups of people. However, respondents were drawn away from these modes, primarily due to safety and budget concerns. Such an observation indicates the need for more protected bike lanes, parking infrastructure, and community outreach programs.

The research findings can serve as a basis for cities to deploy more detailed and large-scale surveys to understand the impact of community emergencies on regional and local transportation networks. However, as the user preferences and perceptions tend to vary with geographic region, caution must be exercised in extending the findings of this study to other regions. This study was conducted a few months before the COVID-19. As the pandemic is widely expected to change the travel demand by traditional and micromobility modes, this study can potentially serve as a valuable baseline for evaluating the variations in mode-choice behavior of Washington DC micromobility users in the post-pandemic environment.

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