Factors Affect People's Intention to Use Micromobility

STAT 579 Final Report
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Abstract

Shared micromobility has been booming in recent years as companies have flooded American cities with micromobility services. With rapid growth of shared micromobility availability and big increases in ridership, it is important to understand factors that drive micromobility usage, as well as assess and manage the impacts of these vehicles and ensure that their benefits are available to all. Using 1774 responses collected from across the U.S., this project seeks to understand how people's intention to use micromobility modes are affected by their attitude and perceptions towards micromobility, as well as social norms. Through explanatory and confirmatory factor analysis, eight latent constructs were identified. A linear regression model is built on these latent variables and results show that people's intention to use micromobility is significantly positively associated with social norm/ influence, expected performance, environmental benefit, perceived risk, and environmental values. People's intention to use micromobility is significantly negatively associated with anti-micromobility attitude. Among all the factors, expected performance has the largest effect. This work can serve as the foundation of understanding people's intention to use micromobility in the US and findings suggest that improving micromobility service systems in terms of their reliability and efficiency are critical for continued growth in usage and ridership.

Introduction

Shared micromobility refers to small, human or electric-powered vehicles, mostly for one passenger only, such as bikes, electric bikes, and electric scooters, shared between multiple users of a service (NACTO 2019; Zarif, Pankratz, and Kelman 2019). Shared micromobility has been booming in recent years as companies have flooded American cities with micromobility services. As of August 2020, 71 docked bikeshare systems are open to the general public, dockless bikeshare systems serve 45 cities, and e-scooters serve 69 cities (BTS 2020). According to reports from the National Association of City Transportation Officials (NACTO), people in the United States took 136 million trips on shared micromobility in 2019, 60% more than 2018, and nearly four times as many as in 2017. With rapid growth of shared micromobility availability and big increases in ridership, it is important to assess and manage the impacts of these vehicles and ensure that their benefits are available to all.

Existing studies have investigated and identified the importance of psychological factors that affect the adoption of micromobility. According to a survey from 11 major U.S. cities, 70% of Americans are supportive of micro-mobility services and perceive shared e-scooters as an alternative to travel without owning a car for short driving trips, or as a complement to public transit (Populus 2018). Studies suggest that performance expectancy, environmental concerns, perceived risk, residual effect (the behavior and experience of the past) are the strongest predictors for intention to use (Eccarius and Lu 2020; Cai et al. 2019; Wang et al. 2021; Kopplin, et al. 2021). Other factors such as social influence, hedonic motivation, and subjective norms also affect the intention to use micromobility services (Chen et al. 2020; Eccarius and Lu 2020; Cai et al. 2019). Most of the studies use factor analysis and structural equation modeling to explore the impacts of latent attitudes and the intention to use micromobility. Through these approaches, mediators, direct, or indirect effects can also be revealed. For example, personal attitudes towards “greenness” and perception of society’s attitude towards bikeshare, moderate the relationship between perceived values and adoption intentions (Wang et al. 2018). The intention to switch from other modes to micromobility is directly affected by relative advantages and compatibility, and indirectly affected by complexity and observability through perceived risk (Wang et al. 2021). Although better trialability may incentivize people to use new shared micromobility at a lower risk, it was not found to have significant influence on prospective users’ risk perceptions or switching intention (Wang et al. 2021).

Based on the literature, this project proposes to understand how people’s intention to use micromobility modes are affected by their attitude and perceptions towards micromobility, as well as social norms.More specifically, this project seeks to answer: (1) What are the underlying structures of people’s norms, perceptions, attitudes, and intention to use micromobility? And (2) What are the factors that affect people’s intention to use shared micromobility?

Data Set Description

Data used in this project is micromobility travel survey data collected by UW Sustainable Transportation Lab. The survey collected responses from 2,564 individuals on Amazon Mechanic Turk (MTurk) across population in the United States (Figure 1). In the psychometric part of the survey, respondents were asked about their norms, perception, attitude, and their intention of using shared micromobility. The survey defined eight upper-level latent construct categories, including social norm/ influence, expected performance, environmental benefit, perceived risk, residual effect, environmental values, (anti)micromobility attitude, and Intention to use micromobility. Three to six indicator questions were identified for each category and in total, respondents were asked 32 psychometric questions. These latent constructs and indicator questions are summarized in Table 1. All of the designed questions were implemented using a six-level Likert scale. The survey also collected socio-economic status of respondents, including age, gender, race, income, household size, and vehicle ownership.

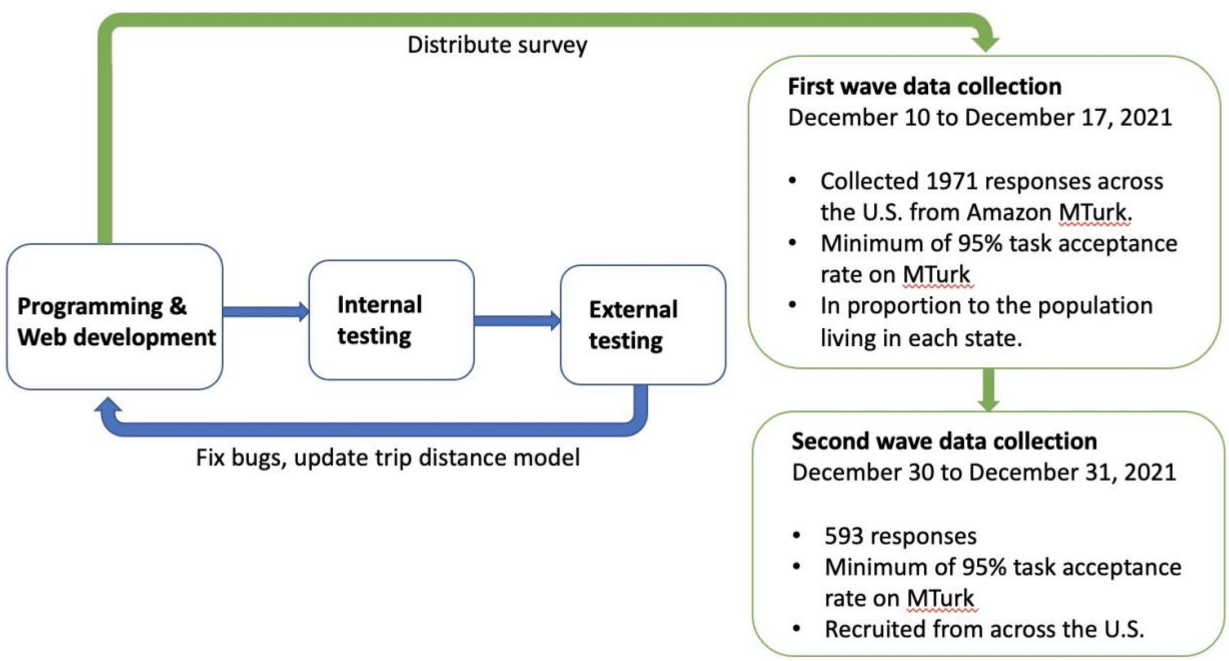

Figure 1. Data collection workflow.

Table 1. A summary of latent variables and psychometric questions.

Psychological variable	Upper-level construct	Question Items
Norms	1.Social norm/ influence	1. My family or friends think using bikesharing or scootersharing is a positive thing.
		2. People important to me think that using bikesharing or scootersharing is a positive thing.
		3. In the near future more people in my city will use bikesharing or scootersharing
		4. People who are important to me think that I should use bikesharing or scootersharing
		5. It is a shame to use bikesharing or scootersharing.
		6. The social media evaluates bikesharing or scootersharing negatively
Perception	2.Expected performance	7. Shared micromobility (eg. Bikesharing, scootersharing) is convenient
		8. Shared micromobility (eg. Bikesharing, scootersharing) is effective for my personal mobility
		9. Shared micromobility (eg. Bikesharing, scootersharing) can help me reach my destination efficiently
		10. There are enough shared bikes/scooters available whenever I want to use them.
		11. I can comfortably take rides on a shared bike or scooter for my daily business
	3.Environmental benefit	12. Using shared micromobility (eg. Bikesharing, scootersharing) will help alleviate traffic congestion
		13. Using shared micromobility (eg. Bikesharing, scootersharing) will reduce carbon emission and air pollution
		14. Using a shared bike or scooter fits my environmental concerns.
		15. Shared micromobility (eg. Bikesharing, scootersharing) has a positive impact on urban traffic.
	4. Perceived risk	16. I would feel safe riding a shared bike or scooter in traffic
		17. I think riding a shared bike or scooter is dangerous.
		18. I would feel nervous about having an accident when riding a shared bike or scooter
	5.Residual effect	19. I knew about bikesharing or scootersharing before
		20. Many people around me know about bikesharing or scootersharing.
		21. I have used bikesharing or scootersharing before.
		22. There are bikesharing or scootersharing available to me, and I can use them regularly.
Attitude	6.Environmental values	23. I would like to do my part to reduce carbon emission and air pollution.
		24. I always consider how my transport choices affect the environment
		25. I consider myself to be an environmentally conscious person.
		26. Global warming is fake science.
	7.(Anti)micromobility attitude	27. Shared micromobility (eg. Bikesharing, scootersharing) is a very bad idea.
		28. Shared micromobility (eg. Bikesharing, scootersharing) causes a lot of problems.
		29. Shared micromobility (eg. Bikesharing, scootersharing) should have not existed in cities.
Intention	8.Intention to use micromobility	30. I'm willing to use bikesharing or scootersharing in the future
		31. I would recommend friends and family to use use bikesharing or scootersharing.
		32. I'm willing to use bikesharing or scootersharing on a regular basis.

Statistical Methods

Data cleaning: Survey responses are collected from MTurk and data cleaning are needed for further analysis.

Descriptive analysis: I'll perform descriptive analysis on the cleaned data and compare the socio-demographic background of respondents to population in the US. In terms of the psychometric questions, I'll summarize the distribution of the answers of each item.

Modeling methods: To answer the first research question, this project proposes to use factor analysis based on the series of observed items described in Table 1 to search for joint variations in response to unobserved latent variables. Although the items are predesigned for given upper-level constructs, it is a relative new field with guides from only a few previous studies. Therefore, I'll first perform an explanatory factor analysis (EFA) to explore the number of factors to extract, and the method (e.g. principal factors, maximum likelihood) and factor rotation (oblique or orthogonal) to extract factors. After obtaining factor loadings and factor correlations in EFA, I'll then perform a confirmatory factor analysis and incorporate the results into a linear regression model with 'Intention to Use Micromobility' as the dependent variable to investigate the second research question. The predictor variables will be latent variables confirmed from CFA.

Results

Data Cleaning

For data cleaning, I excluded incomplete responses and performed quality checks for all completed responses. I first filtered out respondents who reported themselves as younger than 18 years old, consistent with our IRB protocol. I then filtered out ZIP code responses that did not match any official U.S. ZIP code. Next, I checked for contradictory answers on three criteria: (1) Respondents' reported household income should be greater than or equal to their individual income; (2) household size should be larger than the number of children in the household; and (3) when household size is one, household income and individual income should be equal.

I further cleaned the data by validating origin and destination addresses using the Google Maps API as well as manual checking. I filtered out responses where origin or destination input could not be located, or between which no travel route could be found. For responses filtered out by the Google API, manual checking was performed to correct any typographical errors or missing information in address input. Finally, I removed outliers that reported (1) travel time is longer than 240 min; (2) household size is larger than 20; or (3) number of personal vehicles is 20 or more. Figure 2 shows the complete filtering criteria and results. Table 2 summarizes the socio-demographics of the final 1774 responses that passed all quality checks. Table 2 also presents socio-demographic characteristics of the U.S. population from the American Community Survey 2020 (5-year estimates) for comparison.

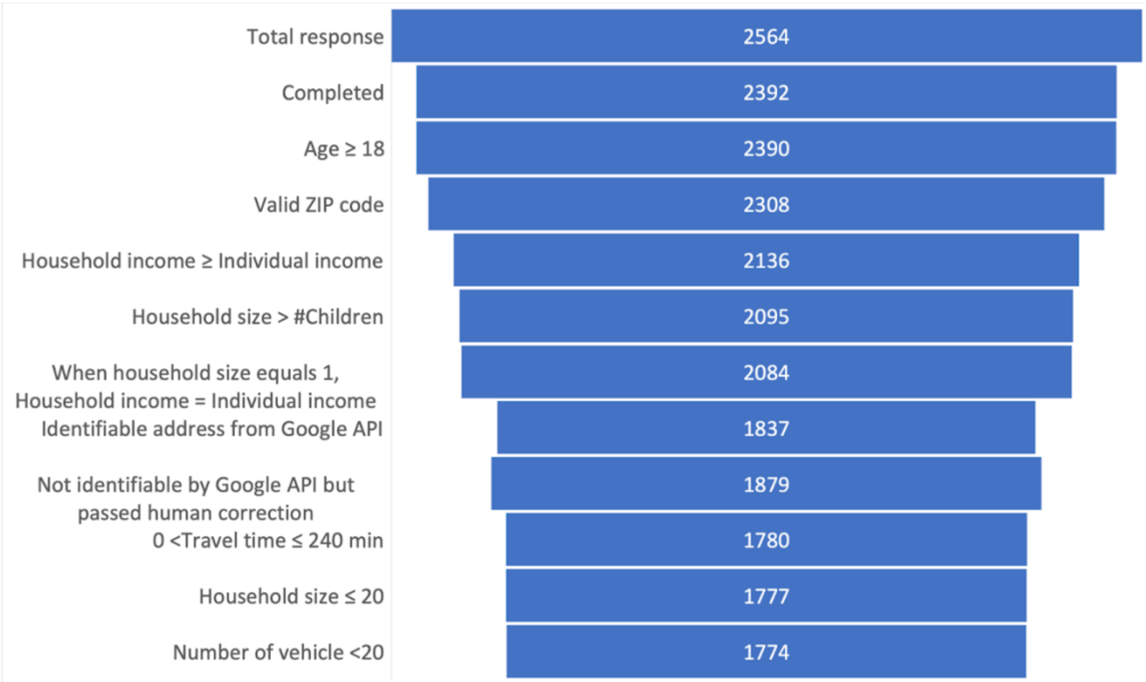

Figure 2. Data cleaning criteria and results.

Table 2. Summary statistics of the 1774 retained respondents, compared with 5-year estimates from 2020 American Community Survey.

Variable	Categories	Respondents	National Population
Age	Age	Min: 18 ; Median: 35; Mean: 38 ; Max: 84	Median:38.2
Gender	Female	42.1%	49.2%
	Male	57.4%	50.8%
	Another	0.5%	
Race	White	81.5%	68.6%
	Black or African American	9.6%	13.8%
	American Indian or Alaska Native	0.8%	1.3%
	Asian	6.3%	6.7%
	Native Hawaiian or Other Pacific Islander	0.1%	0.2%
	Another	1.9%	9.4%
Education Level	Less than bachelor's degree	27.4%	69.6%
	Bachelor's degree and higher	72.6%	30.4%
Employment Status	Employed	90.0%	59.6%
	Not employed	10.0%	40.4%
Household Income Level	Under $25,000	13.8%	18.4%
	$25,000-$49,999	26.2%	20.6%
	$50,000-$74,999	26.2%	17.2%
	$75,000-$99,999	17.5%	12.8%
	$100,000-$149,999	10.5%	15.6%
	$150,000 and up	5.8%	15.4%
Vehicle Ownership	0	4.2%	8.5%
	1	31.1%	32.5%
	2	45.9%	37.1%
	3	12.9%	14.8%
	4 or more	5.9%	7.2%
Total Count	1774 Responses		

Correlation Structure

Correlation structure is very useful for describing the data and important for considering the number of factors in a data set. Figure 3 shows a heatmap of correlations in my data, with darker shades of red representing stronger negative correlations, and darker shades of blue representing stronger positive correlations.

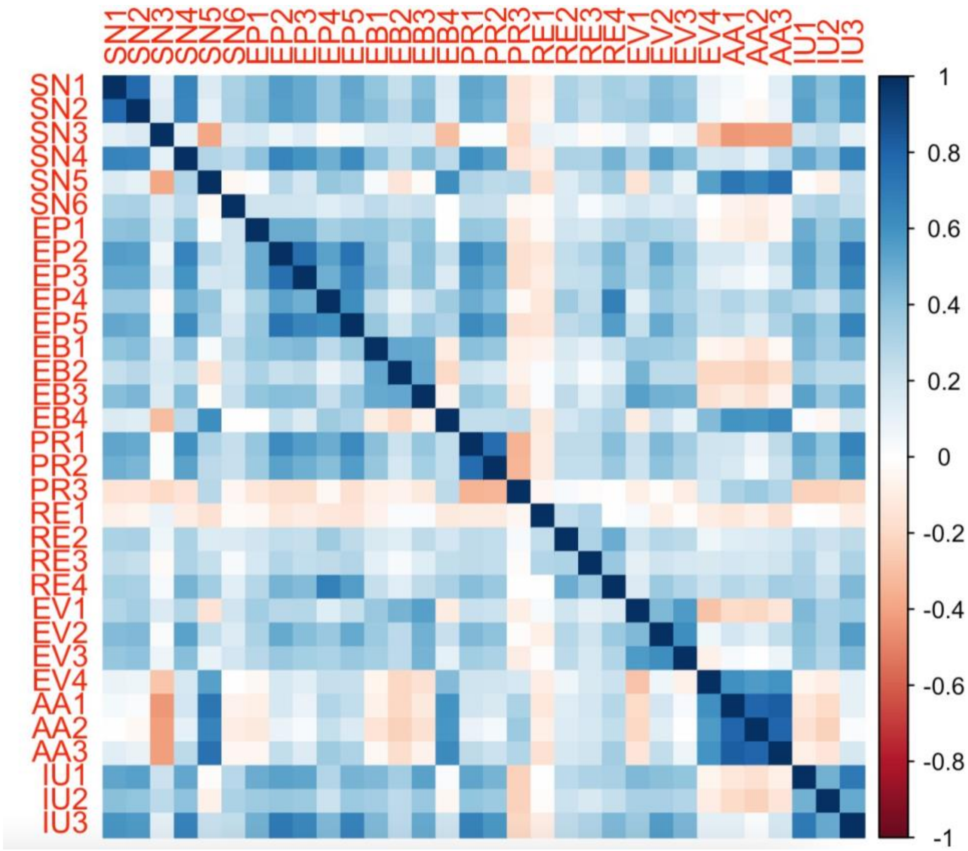

Figure 3. A heatmap showing the structure of correlation matrix.

Determining the Number of Factors to Extract

I first used parallel analysis to determine the number of factors to extract. Although the items are predesigned for fixed number of upper-level constructs, it is a relative new field with guides from only a few previous studies, so I used this data driven approach to explore and compare with my study design. According to Smyth and Johnson (Smyth & Johnson, n.d.), parallel analysis is one of the most common method to analyze optimal number of factors to extract (achieving the most parsimonious but still interpretable factor structure). Figure 4 shows the scree plot of the parallel analysis and the results suggest that the number of factors = 8, which is the same number of upper-level constructs I designed for the survey.

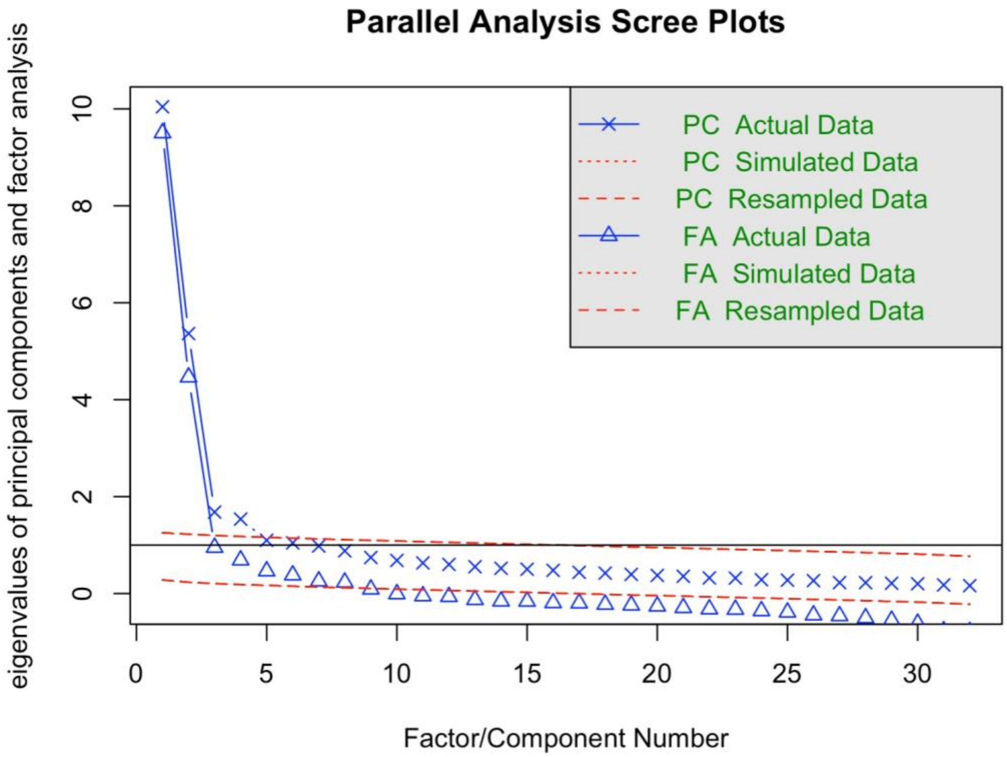

Figure 4. Scree plot from parallel analysis

Confirmatory Factor Analysis (CFA)

Before conducting CFA, EFA, a more data driven approach of understanding the data structure was performed. The results of EFA shows that test of the hypothesis that 8 factors are sufficient. Using a theory driven approach combined with results from EFA and modification indices, CFA was performed to construct a sensible model for factor loading showing below. Table 3 shows the goodness of fit of the CFA model, which suggest an acceptable model fit.

Factor loading:

SN =~ SN1 + SN2 + SN3 + SN4 + SN5 + SN6
EP =~ EP1 + EP2 + EP3 + EP4 + EP5 + EB1
EB =~ EB1 + EB2 + EB3 + EB4
PR =~ PR1 + PR2 + PR3 + AA2
RE =~ RE2 + RE4 + EP4 + EP5
EV =~ EV1 + EV2 + EV3 + EV4
AA =~ AA1 + AA2 + AA3 + SN3 + SN5 + EB4 + EV4 + PR3 + EP1 + IU3 +EV1
IU =~ IU1 + IU2 + IU3

Correlation Specification:

SN1 ~~ SN2
EV1 ~~ EV2
EB1 ~~ EB2
RE2 ~~ RE4

Note: SN = Social Norm; EP = Expected Performance; EB = Environmental Benefits; PR = Perceived Risk; RE = Residual Effects; EV = Environmental Values; AA = Anti-micromobility Attitudes; IU = Intention to Use Micromobility.

Table 3. CFA model goodness of fit.

Degree of Freedom	Chi-square	p-pavlue	RMSEA	SRMR	CFI
361	2077	<0.01	0.05	0.05	0.95

Linear regression

Using latent variables constructed using CFA, a linear regression model is built to understand effects of social norm, perception, and attitude towards micromobility on intention to use them. In the linear model, the dependent variable is latent variable 'Intention to Use Micromobility'. The predictors are other latent constructs confirmed from CFA. Table 4 summarizes the model results.

Table 4. Linear regression model results.

	Estimate	Std.Err	z-value	P(>|z|)
SN	0.291	0.046	6.292	**<0.001**
EP	0.504	0.056	9.006	**<0.001**
EB	0.213	0.062	3.416	**0.001**
PR	0.163	0.019	8.357	**<0.001**
EV	0.134	0.033	4.102	**<0.001**
AA	-0.249	0.018	-13.765	**<0.001**
RE	-0.069	0.053	-1.307	0.191

Intention to use micromobility is mostly affected by Expected Performance (b = 0.504; p <0.001) and secondly Anti-micromobility attitude (b = -0.249; p <0.001). Significantly, Social Norm (b = 0.291; p <0.001), Environment Benefit (b = 0.213; p =0.001), Perceived Risk (b = 0.163; p <0.001), and Environmental Values (b = 0.134; p <0.001) have positive effect on Intention to use micromobility. The effect of Residual Effect is not significantly observed (b = -0.069; p = 0.191)

Discussion

In this project, I used survey response collected from Amazon MTurk across the US to investigate factors affecting people's intention to use micromobility. Compared with the national population, my data sample is skewed towards higher educated people and is less representative for lower income group and the top high-income group. According to results from explanatory analysis, the survey responses sufficiently measure eight latent factors, which is in line with theoretical design of the data collection strategy. A linear regression model indicates that people's intention to use micromobility is significantly positively associated with social norm/

influence, expected performance, environmental benefit, perceived risk, and environmental values. People's intention to use micromobility is significantly negatively associated with anti-micromobility attitude. Among all the factors, expected performance has the largest effect.

Overall, this work can serve as the foundation of understanding people's intention to use micromobility in the US. The results suggest that expected performance is among the most important factors that affect intention to use micromobility. Therefore, improving micromobility service systems in terms of their reliability and efficiency are critical for continued growth in usage and ridership. So far, this project only investigated direct effects. Future work can seek to reveal mediators or indirect effects among the latent psychometric variables through path models and structural equation models.

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