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The Impact of Shared E-Scooters on Travel Behavior in Campus: A Case Study of UCLA

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The Impact of Shared E-Scooters on Travel Behavior in Campus:

A Case Study of UCLA

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by

Kailong Ji

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ABSTRACT OF THE THESIS

The Impact of Shared E-Scooters on Travel Behavior in Campus:

A Case Study of UCLA

by

Kailong Ji

Master of Science in Civil and Environmental Engineering

University of California, Los Angeles, 2024

Professor Tierra Suzan Bills, Chair

The rapid expansion of shared e-scooters has transformed campus transportation, offering an efficient and eco-friendly travel option. This study explores the factors influencing e-scooter usage at UCLA, examining demographic characteristics, user motivations, and the impact of infrastructure interventions. The key challenges include disorderly parking and safety concerns, prompting the need for better planning and management solutions. To address these, we conducted a comprehensive survey and developed nested logit models to analyze travel behavior, focusing on the effects of designated e-scooter parking zones.

Our findings indicate that proper parking management significantly enhances e-scooter acceptance, reduces parking issues, and contributes to better campus transportation efficiency. The study reveals notable differences in travel choices influenced by income, race, and attitudinal factors such as cost consciousness and environmental awareness. Ultimately, our research provides valuable insights for campus administrators and urban planners seeking to optimize micromobility solutions and achieve more inclusive and sustainable urban mobility.

The thesis of Kailong Ji is approved.

Jiaqi Ma

Regan Patterson

Tierra Suzan Bills, Committee Chair

University of California, Los Angeles

2024

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1. Introduction

1.1 Research Background

Since their introduction in the late 19th century, automobiles have become the preferred mode of transportation (Raphael & Rice, 2002). However, as global urbanization accelerates, issues such as traffic congestion and environmental pollution have worsened, driving the development of the micromobility concept (McKenzie, 2020). Shared electric scooters (e-scooters), as an emerging form of micromobility, have rapidly gained popularity in cities worldwide, especially in the United States (Bozzi & Aguilera, 2021). They offer an economical, eco-friendly, and convenient short-distance travel option, particularly in enclosed environments like university campuses where demand and usage have been steadily increasing (Fearnley et al., 2020).

In California, particularly in Los Angeles, the government has actively promoted shared e-scooters through policies such as the Dockless Vehicle Pilot Program and the "Vision Zero" initiative, which allocated $38.5 million for street safety, including micromobility infrastructure, in the 2022-23 fiscal year (Fonseca, 2022). These policies aim to increase the use of micromobility tools, including e-scooters, while reducing traffic congestion and carbon emissions (*E-Scooter Trends and Statistics You Should Know*, 2024). UCLA, as a large urban university with complex transportation needs both on and around campus, has become an ideal setting for shared e-scooter usage.

However, despite the growing use of e-scooters on university campuses, there is a notable lack of attention in transportation and planning literature focusing on campus environments (McKenzie, 2019). Our research aims to explore the factors that influence the use of e-scooters and other modes of transportation through model designs, particularly how proper parking management and route planning can optimize the user experience and mitigate negative impacts, areas that need further exploration (Hollingsworth et al., 2019).

1.2 Research Objectives

The primary objective of this research is to develop a comprehensive understanding of e-scooter usage patterns and user preferences within the UCLA campus community. Through analyzing user behavior, attitudes, and responses to infrastructure changes, this study aims to evaluate the effectiveness of current micromobility policies and identify opportunities for improvement. Specifically, we seek to explore how planning and management measures can optimize e-scooter integration into the campus transportation system, address parking management challenges, enhance safety, and maximize environmental benefits while improving overall campus mobility efficiency.

1.3 Research Questions

This study investigates travel preferences of e-scooter users, using the UCLA Campus community as a case study. By examining travel behavior in this controlled university environment, we seek to gain valuable insights that can inform micromobility implementation in broader urban contexts. The study addresses the following key questions:

- What are the socio-demographic characteristics and usage patterns of micromobility users on the UCLA campus?
- What are the primary motivations for users choosing e-scooters and other modes of transportation? For example, travel time, cost conscious, or racial influences.
- What impact has the implementation of designated e-scooter parking zones had on user behavior, attitudes, and overall campus mobility patterns?

By answering these questions, this research will not only provide scientific evidence for campus administrators to optimize e-scooter user experiences and formulate effective management strategies but will also offer broader insights for transportation planners by using university settings as a testing ground for policies and interventions that can be applied to other urban environments.

1.4 Significance of the Study

As shared mobility models continue to evolve, university campuses serve as ideal micro-environments to study and test these models. Research has shown that lessons learned from campus settings, such as the integration of e-scooters and designated parking zones, can be effectively applied to broader urban contexts, enhancing transportation systems in cities (Bozzi & Aguilera, 2021). This study holds significant practical relevance for transportation policymakers, campus administrators, and urban planners. It provides data to support better promotion and management of e-scooters on campuses. By exploring the potential impacts of e-scooters on student travel behavior, this research will contribute to the development of a more sustainable and eco-friendly campus transportation system. Understanding the usage patterns of e-scooters can help UCLA better plan campus infrastructure, such as determining the optimal locations for designated parking zones, thereby improving students' commuting experiences. Moreover, the scenario model comparison results can offer policymakers effective strategy recommendations to achieve rational allocation and management of transportation tools, reducing congestion and pollution.

In the subsequent chapters, this study systematically examines the following content: Chapter 2 provides a comprehensive literature review of micromobility concepts and their evolution, along with an in-depth analysis of current research on campus micromobility. Chapter 3 employs statistical methodologies to conduct quantitative analyses of survey data, investigating usage preferences and patterns of various transportation modes across different demographic groups, including race, gender, and income levels. Chapter 4 develops Nested Logit (NL) models to analyze how factors such as racial characteristics and cost consciousness influence campus transportation mode choices, while also evaluating the effectiveness of e-scooter parking zone implementation. The final chapter synthesizes the research findings and proposes policy recommendations for improving the management and utilization of campus e-scooter systems.

2. The Growing Significance of Micromobility: Literature Review

2.1 Overview of Micromobility

To address the increasingly severe issues of traffic congestion, environmental pollution, and the need for sustainable transportation solutions in urban areas, Horace Dediu first introduced the concept of micromobility in 2017. Micromobility refers to lightweight, human-powered or electric-powered transportation for short distances, with common examples including e-scooters, bicycles, and e-bikes (Dediu, 2019). As an alternative to traditional transportation modes, micromobility has garnered significant attention globally. The US micromobility market shows significant growth, with shared micromobility trips reaching 133 million in 2023. This represents a year-on-year recovery following Covid-19, nearing the pre-pandemic peak of 136 million trips in 2019. In California, particularly Los Angeles, e-scooters are increasingly prevalent, with the city recording over 5 million shared e-scooter trips in 2023, making it one of the largest shared e-scooter markets in North America (NACTO, 2024). Shared e-scooters have become one of the most popular micromobility tools in cities due to their convenience and environmental benefits, with many cities around the world quickly adopting this mode of transportation (Bozzi & Aguilera, 2021).

Research shows that micromobility, especially e-scooters, plays an increasingly important role in transforming traditional transportation models. E-scooters offer cities an eco-friendly alternative to cars, reducing reliance on fossil fuels and lowering carbon emissions

(Hollingsworth et al., 2019). In densely populated urban areas, e-scooters provide a flexible "Last-Mile" transportation solution, which has also been widely integrated with public transportation systems, allowing users to seamlessly connect to public transit hubs (Shaheen & Cohen, 2020). Additionally, several studies have analyzed the demographics of e-scooter users, revealing that the primary users are aged between 18 and 35. These users choose e-scooters mainly for their convenience, low cost, and sustainability (James et al., 2019; McKenzie, 2019; Sanders et al., 2020).

2.2 Current Research on Campus Micromobility

As the use of e-scooters continues to grow on university campuses, research on micromobility in campus settings is gaining more attention. University campuses, with their high density of people and short-distance travel needs, serve as ideal environments for the promotion of micromobility. Studies have shown that e-scooters provide students and faculty with a convenient, efficient means of travel, reducing reliance on personal vehicles for short trips both on and off-campus (Jafarzadehfadaki & Sisiopiku, 2024).

Numerous campus studies have explored the relationship between shared e-scooters and pedestrian safety, focusing on issues such as improper parking, unsafe riding behavior, and the risks posed to pedestrians on campus (Bozzi & Aguilera, 2021). Some universities have implemented designated parking areas and safety education campaigns to reduce accidents and encourage responsible riding. Studies indicate that the effectiveness of these interventions varies, with some schools reporting improved compliance and fewer accidents, while others still face challenges related to improper usage and insufficient infrastructure (A. Brown et al., 2020; Fang et al., 2018; Glenn et al., 2020).

Additionally, e-scooters have a broader impact on campus transportation systems. Research has found that the popularity of shared e-scooters can encourage students to forgo private vehicles, thereby reducing campus traffic congestion and parking demand (Shaheen & Cohen, 2020). E-scooters have also been found to complement public transit, providing students with a convenient transportation link (Fearnley et al., 2020). However, many campuses still struggle with managing the demand for e-scooters, integrating them into existing transportation networks, and addressing safety and accessibility challenges.

2.3 Research Gaps (Data, Methods, and Insights)

Although the literature on micromobility is increasing, there are still some gaps in research in university campus environments. First, detailed travel activity data on e-scooter usage in campuses remain limited. While many studies in urban environments have revealed usage patterns, data on user's activities patterns (trip chaining), how this is connected to broader travel-related attitudes, and motivations in university settings are relatively scarce (Hollingsworth et al., 2019). Understanding the socioeconomic background and demographic characteristics of users is essential for optimizing the integration of micromobility on campuses.

In particular, important group characteristics and attitudes, such as racial indicators and cost-consciousness, and how these connect to e-scooter usage patterns on campuses, remains unexplored. Understanding how these variables influence students' transportation choices can help campus planners develop more targeted strategies to increase e-scooter usage while supporting fairness in transportation access among different groups (McKenzie, 2020). Furthermore, although some schools have implemented designated parking zones and safety education campaigns, the effectiveness of these policies varies across campuses, highlighting the need for further research on how such policies can be customized to the unique characteristics of each university.

Moreover, there is still insufficient research on how micromobility solutions can be integrated into broader campus planning efforts. While some universities have experimented with e-scooter policies, few have conducted long-term evaluations of infrastructure interventions such as dedicated lanes or charging stations. Shaheen and Cohen (2020) emphasize the importance of conducting these evaluations to ensure micromobility is effectively managed and can achieve sustainable development.

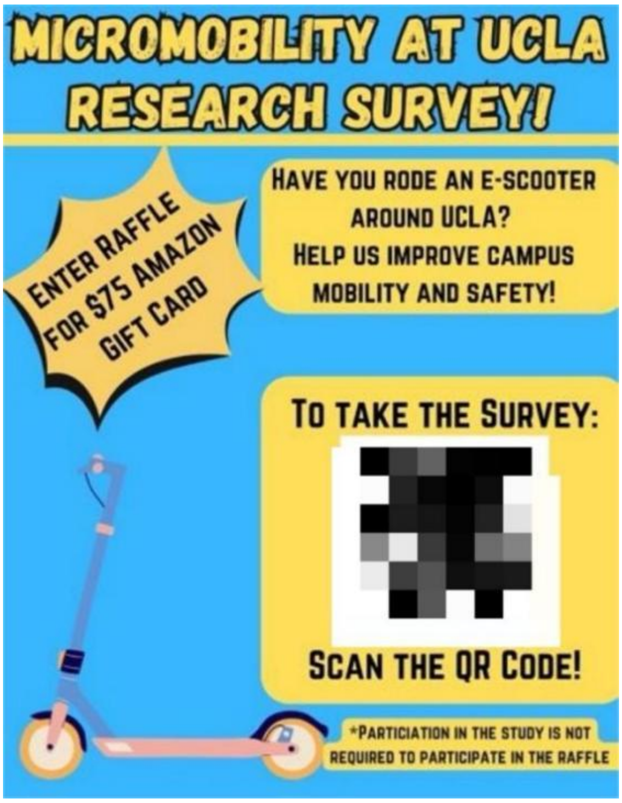
These research gaps present opportunities for further studies, particularly in the application of quantitative models and the collection of detailed behavioral data. Addressing these gaps will not only provide support for campus-level solutions but also offer broader insights for applying micromobility to urban transportation planning.

3. Race, Status, and Attitudes in E-scooter Mode Choice

3.1 Overview of Data Collection Methods

In Spring 2023, we designed and distributed a survey using Qualtrics to provide new and meaningful insights into the rapidly developing field of micromobility. The survey was conducted within and around the UCLA campus by distributing research posters and collecting relevant data. The survey questionnaire consisted of six key sections: demographic information, stated preferences and attitudes, scenarios, and travel mode choices. Each section was carefully designed to capture respondents' behavior and offer detailed insights.

As shown in **Figure 1**, the recruitment flyer included a QR code linked to the survey. The flyers were posted in high-traffic areas on and off campus, such as dormitory lobbies, elevators, off-campus apartments, bike and scooter parking areas, and bulletin boards. To encourage participation, UCLA community members had the chance to enter a raffle to win one of ten $75 Amazon gift cards. Additionally, the flyers were distributed via email and UCLA’s internal communication channels, utilizing a snowball sampling method by encouraging colleagues to share the survey within their networks. During the first three weeks, we received the highest number of responses, likely due to greater student exposure in the middle of the term. Later, as students became occupied with final exams, the response rate declined (**Figure 2**). In total, we received 395 survey responses, of which 243 were used for analysis.



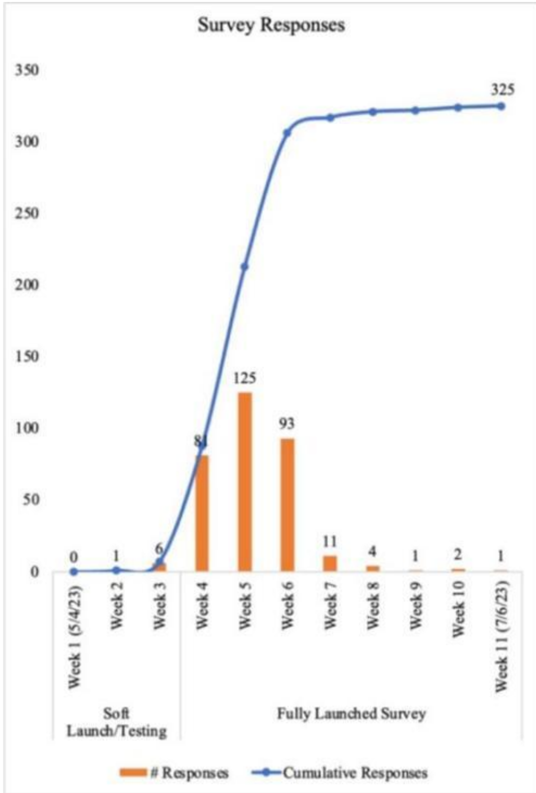


Figure 1: Flyer

Figure 2: Survey Responses

The survey results (**Table 1**) show that the on-campus status distribution of respondents aligns with the overall composition of UCLA's undergraduate and graduate populations. Furthermore, the racial and gender distribution recorded in the survey is generally consistent with the demographics of the student body. This indicates that the sample is representative and reflects the travel modes and e-scooter usage patterns of different groups within the UCLA campus, providing a reliable foundation for further data analysis.

Table 1: Demographic Comparison between UCLA Population and Survey Sample

		Population		Sample	
		Number	%	Number	%
Gender	Male	19,382	41.5%	114	46.9%
	Female	26,438	56.6%	120	49.4%
	Other	858	1.8%	9	3.7%
On-campus Status	Undergraduate Students	33,040	63.4%	151	62.1%
	Graduate Students	13,636	26.2%	59	24.3%
	Administrators/Faculty/Staff	5,464	10.5%	33	13.6%
Race	Black/African Descent	3,026	7.5%	14	5.9%
	Asian	14,432	35.8%	82	34.3%
	White	11,955	29.6%	69	28.9%
	Hispanic	9,111	22.6%	52	21.8%
	Other	1,807	4.5%	22	9.2%

3.2 Demographic Characteristics

To gain a deeper understanding of usage patterns, we conducted a weighted average analysis of travel mode usage frequency (as shown in **Equation 1**) based on the preferences of demographic groups. This comprehensive approach allowed us to explore the relationship between respondents' characteristics and their travel mode choices, offering insights into different groups' preferences for various transportation options. **Table 2** details the weighted usage frequency of different groups.

$$Weight\ Average = \frac{0\times \alpha + 2\times \beta + 5\times \gamma + 7\times \delta}{\alpha + \beta + \gamma + \delta}$$

α = Number of "less than once per week"

β = Number of "1-3 times per week"

γ = Number of "4-6 times per week"

δ = Number of "7 times or more per week"

Equation 1

Table 2: Modal Transportation Usage Frequency Weights

Categorization \ Travel Mode	e-Scooter	Automobile	Bus	Walking	Bike
Gender					
Male	1.905	1.402	1.315	5.455	0.720
Female	1.477	1.825	1.560	4.905	0.531
Other	0.444	1.444	3.000	5.778	0.667
On-campus Status					
Undergraduate Students	2.302	0.832	1.034	5.766	0.624
Graduate Students	0.857	2.339	2.807	4.310	0.776
Administrators/Faculty/Staff	0.000	3.848	1.310	4.219	0.333
Income					
High Income	1.447	1.465	1.328	5.409	0.576
Low Income	1.959	1.691	1.823	5.051	0.705
Middle Income	1.952	1.818	1.350	4.810	0.842
Cost Conscious					
High Cost-Conscious	1.678	1.282	1.647	5.311	0.650
Low Cost-Conscious	1.789	2.952	0.632	5.300	0.429
Middle Cost-Conscious	1.300	2.667	0.947	4.429	0.895
Environmentalist					
High Environmentalist	1.539	1.556	1.633	5.297	0.619
Low Environmentalist	1.625	2.185	1.320	5.120	1.360
Middle Environmentalist	2.167	1.279	1.122	5.047	0.310
Races					
Black/African Descent	1.154	0.929	2.615	5.000	1.385
East Asian	1.674	1.250	1.729	4.938	0.511
Hispanic/Latinx (non-white)	1.200	2.188	1.226	4.906	0.194
Hispanic/Latinx (white)	2.750	1.450	0.947	5.222	0.722
Southeast Asian	3.161	0.971	1.412	5.939	0.333
White	1.092	2.014	1.422	5.328	0.773
Other	0.842	2.045	1.636	4.591	0.800

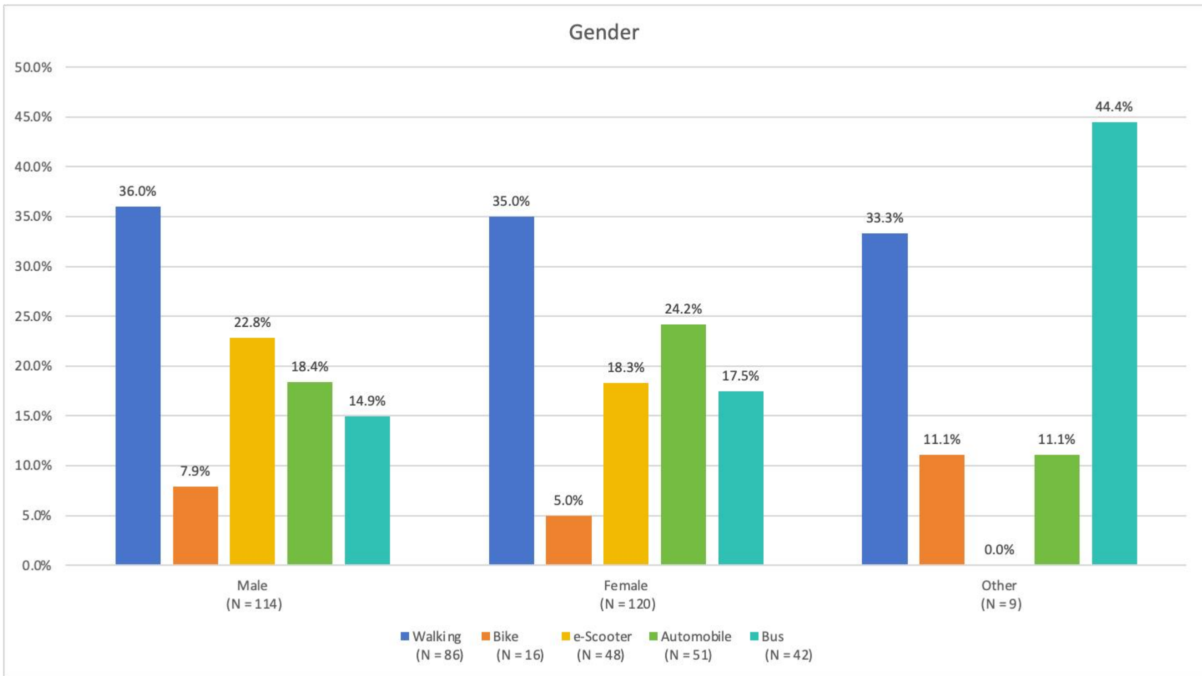


Figure 3: Primary Transportation Mode Choice Distribution by Gender (N=243)

In this small but representative sample, we observe meaningful differences in the use of e-scooters among demographic groups. As shown in **Figure 3**, male respondents reported a 4.5% higher e-scooter usage rate than females, suggesting that men may be more open to adopting and trying this new micromobility option. This finding aligns with previous research indicating that men are more likely to adopt innovative transportation modes. Similar patterns have been observed in other studies. For example, Jennifer Dill's analysis in Portland found that men are more frequent e-scooter users, with men riding more often and perceiving them as a fast and reliable transportation option. Women, on the other hand, expressed greater concern about safety and were more likely to ride in environments with less traffic interaction, such as bike lanes or trails, highlighting infrastructure's role in usage decisions (Dill, 2019). In contrast, women showed a stronger preference for cars (24.2%) and had higher public transit usage (17.5%). Studies on public transit safety indicate that women's preference for cars and public transportation can be linked to safety concerns and the need for more secure travel environments, which influences their lower adoption of newer transportation modes like e-scooters (Ouali et al., 2020).

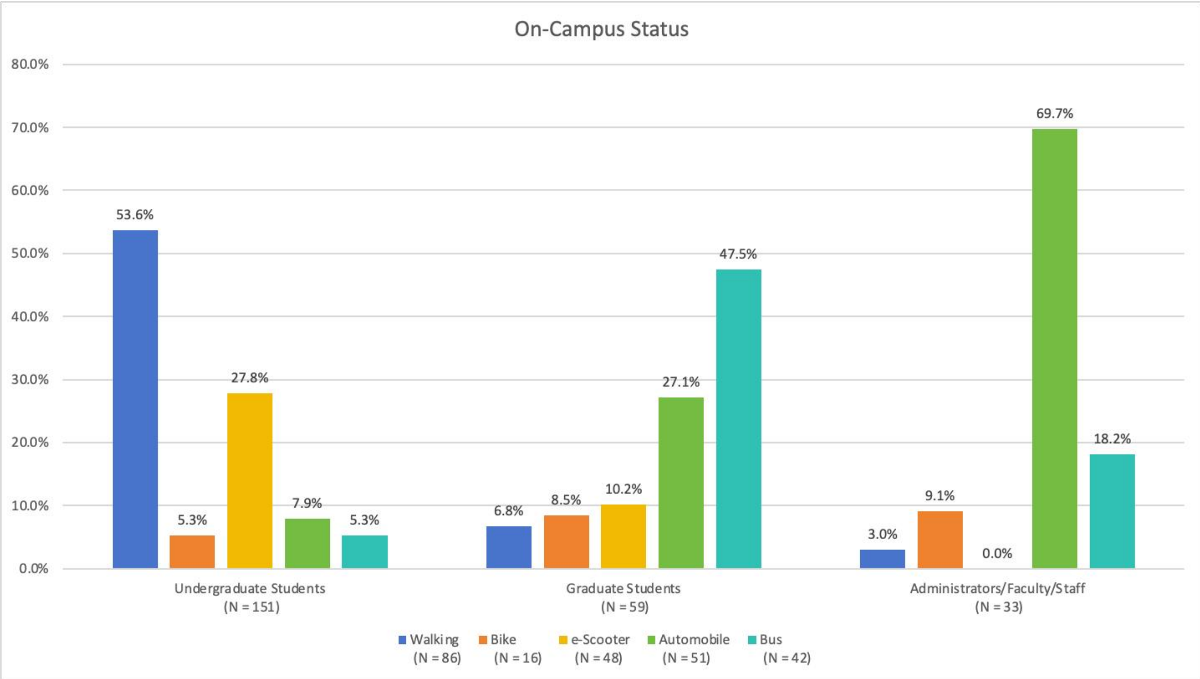


Figure 4: Primary Transportation Mode Choice Distribution by On-Campus Status (N=243)

Educational status also plays a key role in transportation mode choice. As shown in **Figure 4**, 27.8% of undergraduates chose e-scooters as their primary mode of transportation, while graduate students had a lower e-scooter usage rate (10.2%). This suggests that e-scooters are more widely accepted among younger students. Graduate students showed a stronger preference for cars (27.1%) and buses (47.5%), with their weighted usage frequencies being significantly higher than those of undergraduates (Automobile: 2.339 vs. 0.832; Bus: 2.807 vs. 1.034). This difference may also be tied to residential location patterns and travel complexity.

Among graduate students, 86.4% live off-campus, compared to only 32.5% of undergraduates, who mostly reside on-campus (67.5%). Faculty and staff, who all live off-campus, reported no e-scooter usage (0%) and predominantly relied on private cars (69.7%). These patterns suggest that off-campus living, with potentially longer commutes and more complex travel needs, influences transportation choices.

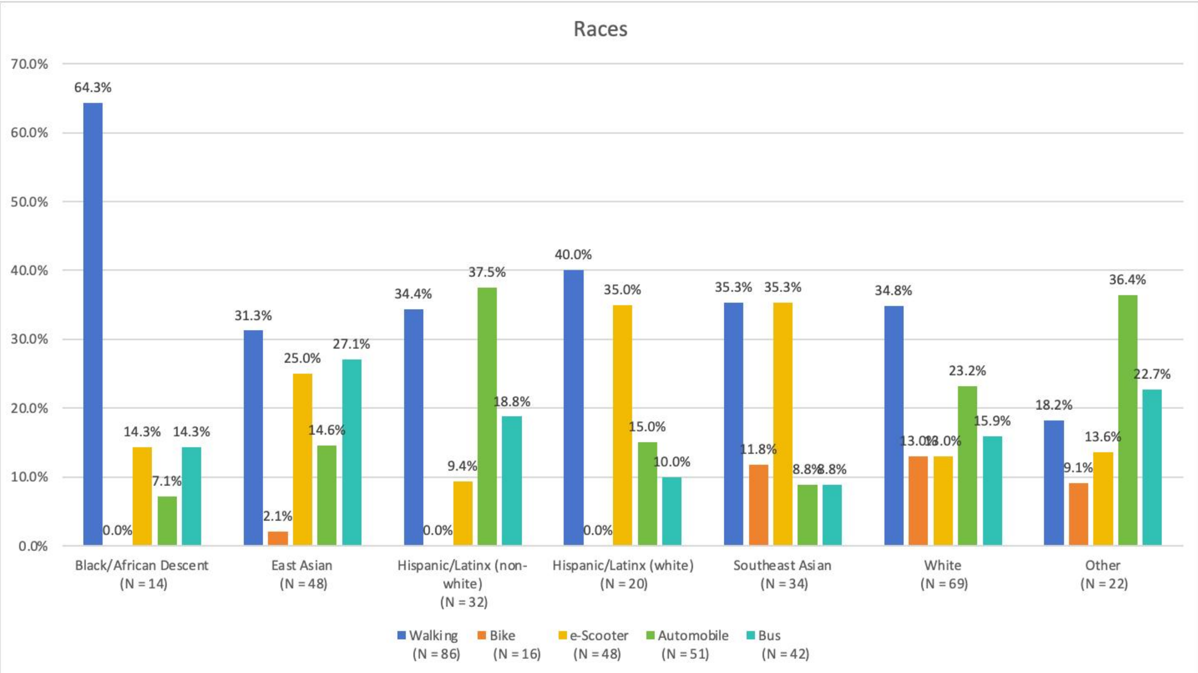


Figure 5: Primary Transportation Mode Choice Distribution by Races (N=239)

Our results suggest that race also plays an important role in travel mode choice. As shown in **Figure 5**, East Asian and Southeast Asian respondents had relatively high e-scooter usage rates, at 25% and 35.3%, respectively. African American respondents reported an e-scooter usage rate of 14.3% but were more likely to walk (64.3%). Among Latinos (excluding White Latinos), 37.5% primarily used cars, with their frequency of car use being higher than other racial groups (2.188), indicating a greater reliance on private vehicles. These findings highlight significant differences in transportation resource usage among racial groups.

3.3 Usage Patterns and Motivations

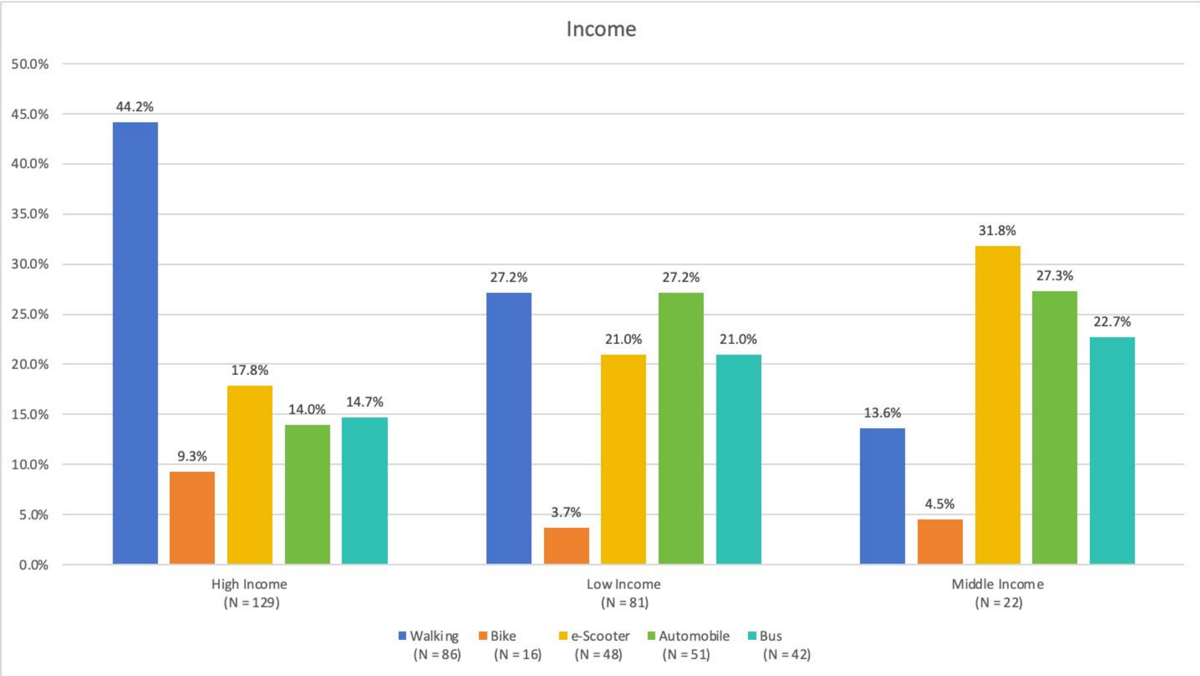


Figure 6: Primary Transportation Mode Choice Distribution by Income (N=232)

Among low-income groups, 21% reported using e-scooters, suggesting that the relative affordability of e-scooters makes them a viable option for these groups. High-income respondents had a slightly lower e-scooter usage rate (17.8%) but were much more likely to walk (44.2%) compared to low-income groups (27.2%). This may reflect the fact that higher-income individuals tend to live within walking distance of UCLA, given the high housing costs in the area. The e-scooter usage rate among economically neutral groups was relatively high (31.8%), possibly reflecting their preference for flexible and environmentally friendly travel modes.

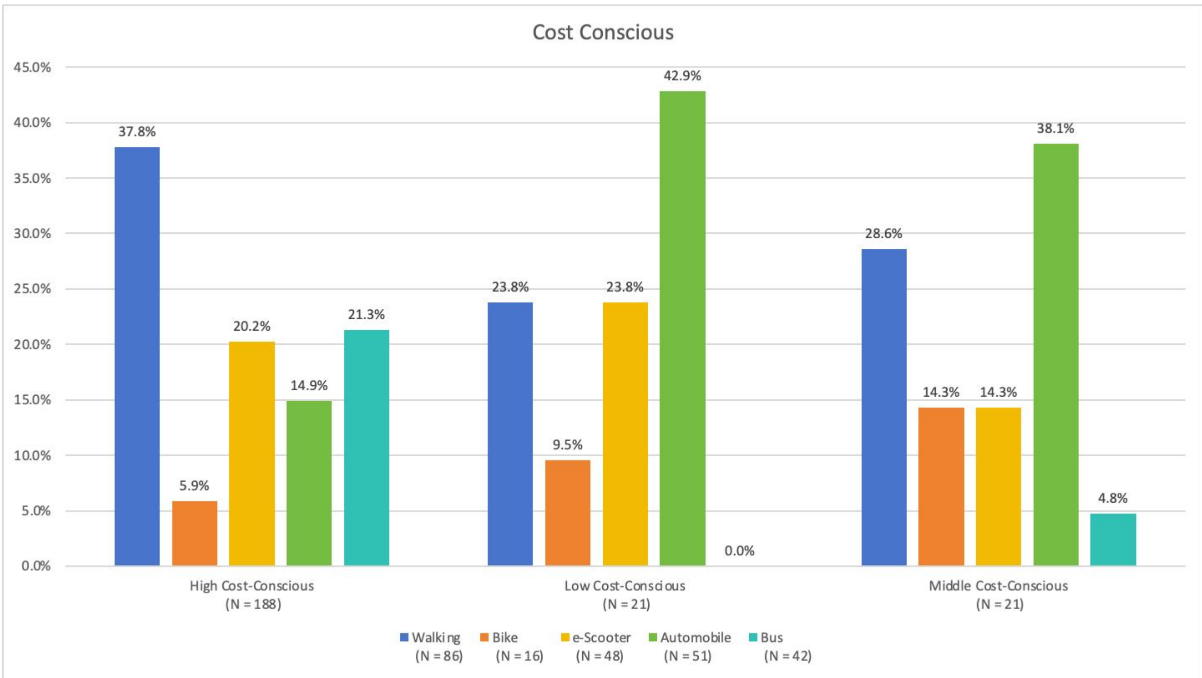


Figure 7: Primary Transportation Mode Choice Distribution by Cost Conscious (N=230)

The analysis suggests a layered interaction between standard demographic variables—such as income, education, and race—and attitudinal variables, such as environmental awareness and cost sensitivity. Cost awareness plays a notable role in transportation mode choice, as shown in **Figure 7**, 20.2% of cost-conscious respondents used e-scooters, compared to 23.8% of those indifferent to costs. However, 42.9% of the cost-indifferent group preferred cars, far higher than the 14.9% among cost-conscious individuals, indicating that financial considerations heavily influence transportation preferences.

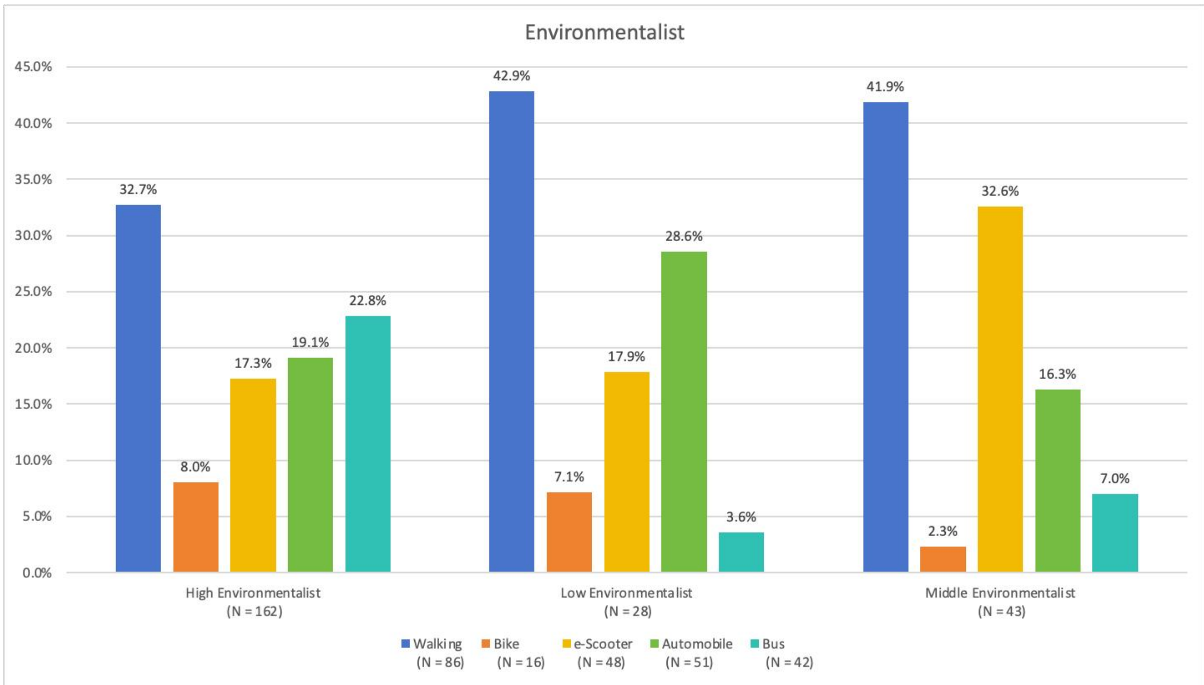


Figure 8: Primary Transportation Mode Choice Distribution by Environmentalist (N=233)

Environmental awareness further influences transportation decisions. As shown in **Figure 8**, among respondents with strong environmental values, 17.3% used e-scooters and 22.8% relied on public transit, reflecting a preference for sustainable travel modes. In contrast, respondents with weaker environmental awareness had higher car usage rates (28.6%) and minimal reliance on public transit (3.6%). These patterns highlight how environmental and financial attitudes shape not only e-scooter adoption but also the broader choice between public and private transportation.

By integrating both demographic and attitudinal variables, this analysis provides a more comprehensive understanding of travel behaviors. While traditional studies often focus on income, education, or race, including factors like environmental and cost awareness offers new insights into how transportation preferences evolve among different student and community groups.

3.4 The Impact of E-Scooters Parking Policy on Travel Behavior and Next Steps

The survey results indicate that the introduction of e-scooters has significantly shaped travel behavior at UCLA. E-scooters are especially effective for “last-mile” travel, providing seamless connections to public transit stops. Additionally, they have reduced dependence on private vehicles, alleviating traffic congestion, and easing parking demand. Differences in transportation choices highlight the influence of economic status, race, and environmental awareness on mobility preferences.

However, the growing number of e-scooters has led to parking challenges, disrupting campus order, posing safety risks, and making it more difficult for users to locate available devices. To mitigate these issues, establishing designated parking zones has been proposed as a solution. Research indicates that parking zones help organize micromobility devices, reducing sidewalk obstructions and safety hazards. However, while such zones improve order, they may also limit the flexibility and convenience that users value, potentially discouraging shared e-scooter use (Shaheen, 2019).

Micromobility policies on campuses show that integrating infrastructure such as scooter parking corrals can address clutter and enhance compliance (Shaheen, 2019). These interventions promote proper parking through both digital tools (e.g., geofencing) and physical infrastructure (e.g., street corrals) (*Parking & Street Design – Shared Micromobility Playbook*, n.d.). However, urban and campus environments must achieve an equilibrium between accessibility and regulation to ensure the sustainable adoption of micromobility solutions.

To evaluate the potential impact of designated parking zones, we employ a two-stage modeling approach. In the first stage, we develop a baseline Nested Logit (NL) model to capture current campus travel preferences and mode choice behavior. This base model is progressively enhanced by incorporating factors such as cost consciousness and racial characteristics to identify key determinants of transportation choices across different user groups, ultimately selecting the most robust model specification. In the second stage, we extend the optimal model to include parking zone scenarios, examining how these baseline preferences might shift in response to the new infrastructure. Through comparing these models, we can systematically assess how the implementation of designated parking areas influences user behavior, mode choice decisions, and overall campus mobility patterns.

4. Race and Status Indicators in Campus Travel Behavior Models

4.1 Methods

To investigate travel behavior patterns among UCLA community members and understand how these patterns vary across racial groups and attitudinal factors, we developed a series of unordered discrete choice models. In transportation behavior modeling, both ordered and unordered discrete choice methods are commonly used, with Multinomial Logit (MNL) and Nested Logit (NL) models gaining popularity for their analytical flexibility and long-term applicability.

Bhat and Pulugurta (1998) found that NL models outperform MNL models in predictive accuracy and goodness of fit. NL models are particularly effective at managing complex hierarchical decisions, making them suitable for analyzing behavioral patterns across income levels in transportation choices (Train, 2002). Sabouri et al. (2021) further emphasized that NL models provide higher adaptability when modeling complex, multi-layered transportation decisions. Based on these findings, this study employs NL models to evaluate the impact of designated e-scooter parking zones on travel behavior.

For transportation mode choices, we included only Walk, Bike, e-Scooter, and Drive. Due to data limitations in the original survey, where key bus attributes such as transfers and waiting times were not captured, bus transportation was classified under the "other" category.

To ensure methodological robustness, we evaluated both MNL model and NL model specifications. Initial testing revealed that the MNL model's key parameters lacked statistical significance, suggesting its inadequacy in capturing the complex travel behavior patterns in our study context. Subsequently, we implemented a two-nest structure (illustrated in **Figure 9**), which proved effective in accounting for unobserved heterogeneity in traveler preferences ——an aspect that the MNL model specification failed to capture.

4.1.1 Utility Function of the Nested Logit (NL) Model

A nested logit model is appropriate when the set of alternatives faced by a decision-maker can be partitioned into subsets, called “nests”, in such a way that the following properties hold. (1) For any two alternatives that are in the same nest, the ratio of probabilities is independent of the attributes or existence of all other alternatives. That is, independence of irrelevant alternatives (IIA) holds within each nest. (2) For any two alternatives in different nests, the ratio of probabilities can depend on the attributes of other alternatives in the two nests. IIA does not hold in general for alternatives in different nests.

Without loss of generality, the observed component of utility can be decomposed into two parts: (1) a part labeled W that is constant for all alternatives within a nest, and (2) a part labeled Y that varies over alternatives within a nest. Utility is written as:

$$U_{nj} = W_{nj} + Y_{nj} + \varepsilon_{nj}$$

Equation 2

For $j \in B_k$, where:

W_{nk} depends only on variables that describe nest k. These variables differ over nests but not over alternatives within each nest.

Y_{nj} depends on variables that describe alternative j. These variables vary over alternatives within nest k.

Where W_{nj} is the observable component of the utility, typically expressed in linear form as:

$$W_{nk} = \beta_0 + \beta_1 x_{1nk} + \beta_2 x_{2nk} + \ldots\ldots + \beta_m x_{mnk}$$

Equation 3

In this formula, β_n represents the parameters to be estimated, and X_{mnj} denotes the variables associated with individual n's choice of alternative k, such as travel cost, time, and racial background. ε_{nk} is the random error term, capturing unobserved factors and individual heterogeneity.

For this transportation mode choice model, let U_{nj} represent the utility of individual i choosing alternative j, where $j=1$ represents choosing Walk as the primary mode of transportation, $j=2$ represents Bike, $j=3$ represents e-Scooter, and $j=4$ represents Drive.

4.1.2 Choice Probability in the Nested Logit Model

The NL model divides the choice set into multiple nests B_m, where each alternative belongs to a specific nest $B(J)$. The choice probability P_j can be decomposed into two parts: the conditional probability of selecting an option within a given nest $B(J)$ and the probability of choosing the nest $B(J)$ itself.

$$B(J) = \{B_m : j \in B_m,\ m = 1, 2, \ldots M\}$$

Equation 4

For this transportation mode choice model, **Figure 9** illustrates a potential nested structure. The number of nests is M = 2. The respondents are categorized by income level into two nests:

Active Modes Nest: $B_{Active\ Modes} = \{Walk, Bike\}$

Motorized Modes Nest: $B_{Motorized\ Modes} = \{e\text{-}Scooter, Drive\}$.

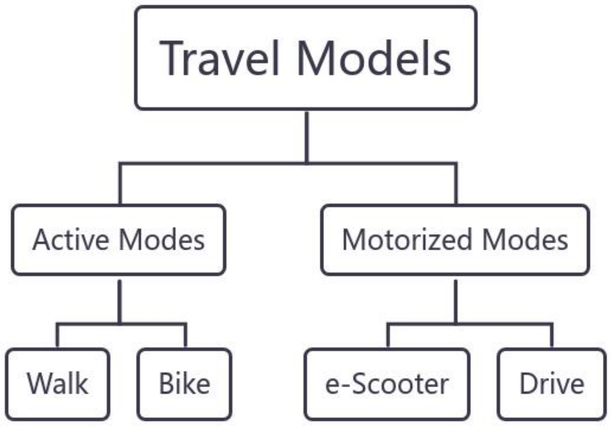


Figure 9: Nesting structure for models

With this decomposition of utility, the nested logit probability can be written as the product of two standard logit probabilities. Let the probability of choosing alternative $i \in B_k$ be expressed as the product of two probabilities, namely: the probability that an alternative within nest B_k is chosen and the probability that the alternative i is chosen given that an alternative in B_k is chosen. This is denoted as

$$P_{ni} = P_{ni|B_k} * P_{nB_k}$$

Equation 5

The term $P_{ni|B_k}$ represents the conditional probability of selecting a specific option j within a given nest B_k. This probability follows the structure of the classic MNL model.

$$P_{ni|B_k} = \frac{e^{Y_{ni}/\lambda_k}}{\sum_{j \in B_k} e^{Y_{nj}/\lambda_k}}$$

Equation 6

In this context, λ_k is the dissimilarity parameter, which measures the degree of similarity among options within the same nest. A smaller λ_k indicates that the options within the nest are more similar. Louviere et al. (2000) reframe this parameter as $\mu_m = 1/\tau_m$.

The choice probability among nests also P_{nB_k} follows the structure of the MNL model:

$$P_{nB_k} = \frac{e^{W_{nk} + \lambda_k I_{nk}}}{\sum_{l=1}^{K} e^{W_{nl} + \lambda_l I_{nl}}}$$

Equation 7

Where I_{nk} represents the inclusive value of nest B_k. It corresponds to the expected utility that individual i derives from the alternatives within nest k, serving as an aggregate measure of the attractiveness of all options in that nest.

$$I_{nk} = ln \sum_{j \in B_k} e^{Y_{nj}/\lambda_k}$$

Equation 8

The inclusive value reflects the overall attractiveness of all alternatives within the nest and is used to model the choice between nests.

$$P_{ni} = P_{ni|B_k} * P_{nB_k}$$

(Equation 5)

$$P_{ni} = \frac{e^{Y_{ni}/\lambda_k}}{\sum_{j \in B_k} e^{Y_{nj}/\lambda_k}} * \frac{e^{W_{nk}+\lambda_k I_{nk}}}{\sum_{l=1}^{K} e^{W_{nl}+\lambda_l I_{nl}}}$$

Equation 9

$$P_{ni} = \frac{e^{V_{ni}/\lambda_k} (\sum_{j \in B_k} e^{V_{nj}/\lambda_k})^{\lambda_k - 1}}{\sum_{l=1}^{K} (\sum_{j \in B_l} e^{V_{nj}/\lambda_l})^{\lambda_l}}$$

Equation 10

The nested logit model demonstrates significant advantages in capturing correlations among unobserved factors influencing travelers' mode choices. Through its hierarchical structure of grouping similar alternatives, the model offers enhanced flexibility in addressing complex choice scenarios with highly correlated options. This methodological approach is particularly well-suited for understanding the inherent interdependencies in transportation behavior (Train, 2002).

4.1.3 Model Evaluation

The baseline model serves as a foundation for subsequent model development, enabling clear comparisons of how different factors influence individual mode choice behavior. Building upon this foundation, we incorporated additional variables, including cost consciousness and racial characteristics, to examine their moderating effects on transportation mode choices.

To assess the information gain from incorporating racial and cost consciousness indicators into the campus micromobility model, we analyzed model fit statistics and conducted likelihood ratio tests between models using the formula $LR = -2(L_1 - L_2)$, as shown in **Table 6.** Here, L_1 represents the maximum likelihood value of the more parameterized model, while L_2 denotes the maximum likelihood value of the less parameterized model.

4.2. Model Specifications

Table 3 presents the details of various variables used for calculation and analysis in the model. Variables and attributes are categorized into three major categories: travel scenario variables, race and ethnicity indicators, and scale factors between nested structures. In addition, we have introduced individual behavioral preference variables to delve deeper into the impact of respondents' subjective preferences on travel mode choice.

Table 3: Definitions of variables

Variable		*Type*	*Definition*
Travel Scenario			
Walk Time	Walk Travel Time	Continuous	Number of walking travel time
	e-Scooter Walk Time	Continuous	Number of walking times associated with e-scooter use, such as walking to the parking area
	Drive Walk Time	Continuous	Number of walking times associated with car use, such as walking to the parking area
Travel Time	Bike Travel Time	Continuous	Number of commuting times by bicycle
	e-Scooter Travel Time	Continuous	Number of commuting times by e-scooter
	Drive Travel Time	Continuous	Number of commuting times by car
Travel Cost	e-Scooter Travel Cost	Continuous	Number of e-scooter travel costs, such as fees for renting shared e-scooters
	Drive Travel Cost	Continuous	Number of car travel costs, such as parking fees and fuel expenses
Individual level characteristics			
Income	Low Income	Dummy	=1 if the respondent considers themselves from a low-income household
	High Income	Dummy	=1 if the respondent considers themselves from a High-income household
Cost Conscious	High cost-conscious	Dummy	=1 if they care about transportation costs
	Low cost-conscious	Dummy	=1 if they do not care about transportation costs
Race	Black African Descent	Dummy	=1 if the respondent is African American
	East Asian	Dummy	=1 if the respondent is East Asian
	White	Dummy	=1 if the respondent is white
	Hispanic non-White	Dummy	=1 if the respondent is Hispanic non-white
	Hispanic White	Dummy	=1 if the respondent is Hispanic white
	Southeast Asian	Dummy	=1 if the respondent is Southeast Asian
Other			
e-Scooter Dependency		Dummy	=1 if choosing e-scooter travel, specifically using a shared e-scooter
Scales (μ)	Active Modes	Continuous	Scale of the Active Modes nest
	Motorized Modes	Continuous	Scale of the Motorized Modes nest

4.3 Results

4.3.1 Comparison of Results for Different Models of Campus Travel Modes

To delve deeper into the influencing factors of campus micromobility, we constructed four different nested logit specifications and perform a series of integrative comparisons. These models are estimated using Python Biogeme (Bierlaire, 2023). The choice set includes alternatives such as Walk, Bike, e-Scooter, and Drive. Due to the relatively small number of individuals choosing cycling as their preferred mode of transportation, we set cycling as the base option. Positive parameter estimates indicate a positive influence of a factor on a specific travel mode, while negative parameter estimates suggest a negative influence, meaning that the higher the value, the lower the probability of choosing that mode. The model specifications are shown in **Figure 10**. The estimated results are shown **Table 4**.

We conducted likelihood ratio tests (LRT) to compare the goodness-of-fit across the model specifications. The results are shown in **Table 6**. Overall, the LRT results indicate that the composite model (including indicators of race and cost consciousness) offers higher explanatory power, beyond the comparison modes (A-C). These are discussed in more detail in **4.3.2. Evaluation of Models.**

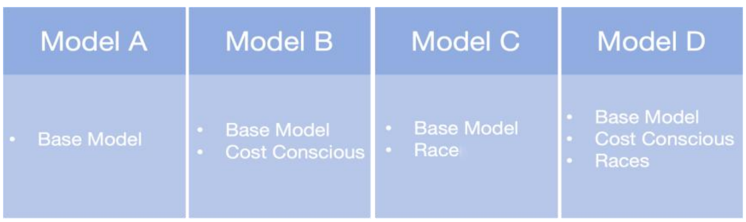


Figure 10: Models Flow Chart

Table 4: Estimation Results of Campus Micromobility Model

			Model A	Model B	Model C	Model D
Variables		Travel Modes	Base Model	Model A + Cost Conscious	Model A + Race	Composite
Alternative Specific Constant	ASC_Walk		2.581 (3.387)	1.978 (2.68)	1.372 (2.624)	1.053 (1.975)
	ASC_Bike		NA	NA	NA	NA
	ASC_e-Scooter		2.585 (3.443)	2.867 (3.678)	1.395 (3.152)	1.848 (3.579)
	ASC_Drive		1.945 (2.452)	2.205 (2.687)	-	1.177 (1.986)
Travel Scenario						
	Travel Time		-0.021 (-4.276)	-0.026 (-4.557)	-0.018 (-3.264)	-0.022 (-3.537)
	Walk Time		-0.044 (-4.94)	-0.045 (-5.002)	-0.03 (-2.626)	-0.034 (-2.944)
	Travel Cost		-0.014 (-2.009)	-0.015 (-1.999)	-0.014 (-1.971)	-0.016 (-2.018)
	e-Scooter Dependency		-1.984 (-11.576)	-2.123 (-11.98)	-1.818 (-9.099)	-1.957 (-9.879)
Individual level characteristics						
Cost Conscious	High Cost Conscious	Walk	NA	1.535 (8.572)	NA	1.501 (6.542)
		Bike		1.101 (7.728)		0.554 (1.982)
	Low Cost Conscious	e-Scooter		1.591 (3.355)		1.328 (2.273)
		Drive		1.615 (4.259)		1.418 (3.363)
Ethno-racial Groups	Black African Descent	Walk	NA	NA	0.759 (3.059)	0.59 (2.235)
		Bike			-7.532 (-4.444)	-7.444 (-4.165)
		e-Scooter			-	-
		Drive			-	-
	East Asian	Walk	NA	NA	-	-
		Bike			0.756 (2.011)	0.844 (1.958)
		e-Scooter			0.406 (2.403)	0.397 (2.195)
		Drive			-0.564 (-3.029)	-0.584 (-2.977)
	White	Walk	NA	NA	-	-
		Bike			-	-
		e-Scooter			-0.422 (-2.489)	-0.484 (-2.671)
		Drive			0.477 (3.117)	0.372 (2.287)
	Hispanic Non-White	Walk	NA	NA	-	-
		Bike			-	-
		e-Scooter			-	-
		Drive			-0.536 (-2.407)	-0.525 (-2.224)
	Hispanic White	Walk	NA	NA	-	-
		Bike			-8.619 (-3.701)	-9.685 (-2.893)
		e-Scooter			-	-
		Drive			-	-
	Southeast Asian	Walk	NA	NA	-0.5 (-3.166)	-0.621 (-3.864)
		Bike			0.88 (2.919)	0.914 (3.039)
		e-Scooter			0.416 (2.115)	0.465 (2.174)
		Drive			-	-
Other						
Nest Scales (μ)	Motorized Modes		2.278 (6.494)	3.215 (6.497)	3.065 (5.103)	2.798 (5.257)
	Active Modes		1.833 (3.163)	1.853 (3.113)	1.025 (2.822)	1.270 (2.885)
	Time Value ($/hr)		40.00	34.62	46.67	43.64
Number of observations (N)			1368	1368	1368	1368
Null log-likelihood (L(0))			-1896.451	-1896.451	-1896.451	-1896.451
Model log-likelihood (L(b))			-1421.01	-1381.295	-1411.945	-1373.568
Rho-squared			0.251	0.272	0.255	0.276
Adjusted rho-squared			0.246	0.266	0.248	0.267

Note: t-statistic in parentheses; NA = not applicable; “—" = coefficients are insignificant at 90% confidence interval

The baseline **Model A** is an attributes-only specification; with alternative specific constants (ASC), and travel time and travel cost. The constants for walking, e-scooter, and drive alternatives are all positive, indicating that these modes are generally preferred relative to bike. The coefficients for travel time and cost are both negative and significant, as expected, indicating that the attractiveness of these modes decreases as travel time and cost increase.

This is consistent with the theory of behavioral economics, which suggests that people tend to weigh time and economic costs when choosing transportation modes to seek the optimal travel experience (Thaler & Sunstein, 2008).

In **Chapter 3**, our descriptive analysis found that cost consciousness has a significant impact on transportation mode choice, and this is tested in **Model B**. The results for Model B suggest high cost-consciousness have a positive relationship with low- cost travel modes. The coefficients for walking and cycling are 1.535 and 1.101, respectively. These positive parameter values indicate that travelers who are very cost conscious are more likely to choose these low-cost or free modes of transportation. For the low-cost conscious travelers, their coefficients for e-scooters and private cars are 1.591 and 1.615, respectively. These positive parameter values indicate that despite the higher cost of these modes of transportation, low cost-consciousness groups may place more emphasis on convenience than economic cost.

Model C introduces racial characteristics, with African Americans serving as the reference group, to analyze differences in transportation mode choice among different racial groups. The results suggest that African Americans and Hispanic whites are significantly less likely to use e-scooters and drive, relative to other groups. May be due to a combination of factors such as inadequate community infrastructure, concerns about traffic safety, cultural habits, and economic conditions (C. T. Brown & Sinclair, 2017; Lee et al., 2017). When formulating policies, it is necessary to pay attention to the practical difficulties faced by African Americans and provide them with safer and more convenient bicycle infrastructure and support (Golub et al., 2016). Further, the results suggest, East Asian and Southeast Asian groups have a strong and positive preference for e-scooters. White travelers seem to have a higher relative preference for driving and a negative preference for e-scooters. This result may reflect their uniqueness in travel mode: white groups may live more in suburbs or low-density communities, leading to a greater reliance on cars (Taylor & Ong, 1994), while e-scooters are less applicable in these areas. Hispanic non-whites only show a significant negative preference for cars (-0.536). This group lives more in high-density urban areas, where walking, cycling, or public transportation may be more convenient than cars (Taylor & Ong, 1994).

Model D is a comprehensive model that combines cost consciousness, racial characteristics, and other individual characteristics as independent factors. The results show that both cost consciousness and racial characteristics maintain significant effects on mode choice in this integrated model, though their preference parameters have changed, reflecting the complex nature of mode choice behavior. For example, individuals with low cost-consciousness consistently prefer e-scooters and driving, while the bicycle preference among high cost-consciousness individuals appears weaker in Model D. These findings suggest potential underlying relationships between socioeconomic characteristics in influencing mode choice. Future research could explore interaction effects between racial characteristics and cost consciousness to better understand how these factors might jointly influence transportation mode decisions.

The analysis of Model D highlights the complex interplay between multiple factors and shows how these factors collectively shape individual travel choice behavior. By considering the combined impact of multiple variables, the study reveals deeper driving factors behind mode choice. For example, individuals with high cost-consciousness may experience changes in their choice preferences when faced with the interactive effects of racial characteristics, further illustrating the multidimensionality of travel choice and the underlying socioeconomic complexity.

4.3.2 Probability of campus travel models

As shown in **Table 5**, through the analysis of four progressive models, we found that the probability of choosing a mode of transportation changed significantly as new variables were gradually introduced into the model. Comparing these model predictions with the true observed probabilities provides insights into each model's predictive accuracy and the importance of different variables

Table 5: Probability of campus travel models

	P_Walk	P_Bike	P_eScooter	P_Drive
True Probability	42.79%	7.96%	23.88%	25.37%
Model A	50.96%	5.19%	23.81%	20.04%
Model B	44.35%	4.93%	27.46%	23.26%
Model C	49.84%	17.12%	24.94%	8.10%
Model D	46.33%	10.05%	24.69%	18.93%

The true observed probabilities show that walking accounts for 42.79% of transportation choices, followed by driving (25.37%), e-scooters (23.88%), and biking (7.96%). The base model (Model A) predicts a 50.96% probability of walking, showing some overestimation, while its predictions for e-scooters (23.81%) align remarkably well with the observed value (23.88%). However, it underestimates both biking (5.19% vs. true 7.96%) and driving (20.04% vs. true 25.37%). These differences suggest that basic travel time and cost factors alone, while capturing some fundamental patterns, cannot fully explain the complexity of mode choice behavior, particularly for modes requiring more specific infrastructure or involving unique user preferences.

Model B demonstrates notable improvements compared to Model A in its predictive capabilities. The probability prediction for walking decreased from 50.96% to 44.35%, aligning more closely with the observed value of 42.79%, indicating that the newly incorporated cost-conscious variable effectively captures pedestrian mode choice factors. Similarly, the driving prediction improved from 20.04% to 23.26%, approaching the actual value of 25.37%. However, certain predictive discrepancies persist, bicycle usage prediction slightly decreased from 5.19% to 4.93%, showing significant underestimation compared to the observed 7.96%, suggesting that some critical factors influencing bicycle choice remain insufficiently addressed in the model. Notably, the e-scooter usage prediction increased from 23.81% to 27.46%, deviating from the observed value of 23.88%, indicating potential over-emphasis of certain variables affecting micro-mobility choices. While Model B exhibits improved predictions for major competing modes, the persistent underestimation of bicycle use and decreased accuracy in e-scooter predictions suggest the need for further optimization in variable weighting and model specification.

After incorporating racial factors in Model C, we observe notable shifts in predicted probabilities. The walking share increases to 49.84%, moving away from the true value, while bicycle use rises substantially to 17.12%, considerably higher than the observed 7.96%. This overestimation of bicycle use might reflect the model capturing strong preferences for cycling among certain demographic groups but not fully accounting for practical constraints like bicycle availability or infrastructure. The e-scooter prediction (24.94%) remains relatively close to the actual share, suggesting that racial factors have less impact on e-scooter choices. However, the driving prediction drops significantly to 8.10%, far below the true value of 25.37%, indicating that the model might be overemphasizing the role of racial preferences in driving choices while underestimating other important factors like residential location or cost conscious.

When considering all variables simultaneously in Model D, we see some improvement in overall predictions. The walking probability (46.33%) remains somewhat elevated but closer to the true value than Model C, suggesting that the combination of variables helps balance out some of the overestimation effects. The bicycle share (10.05%) and driving share (18.93%), while still not perfectly aligned with observed values, show improvement compared to Model C's extreme predictions. The e-scooter prediction (24.69%) maintains its accuracy near the true share, demonstrating remarkable stability across model specifications. These results suggest that while incorporating multiple factors helps capture various influences on mode choice, the relationship between these factors is complex and may require more sophisticated modeling approaches to achieve better predictive accuracy. The consistent accuracy in e-scooter predictions across models might indicate that e-scooter choice behavior is more straightforward to model, possibly because it's less influenced by complex socioeconomic factors.

It is particularly noteworthy that the impact of walking time. In all models, the negative coefficient of walking time (ranging from -0.034 to -0.045) is consistently greater than the negative coefficient of general travel time (-0.022). This difference suggests that people are more sensitive to the time spent walking than other modes of transportation. In other words, the same increase in time, if it is an increase in walking time, will lead to a greater reduction in people's likelihood of choosing that mode of transportation.

4.3.2. Evaluation of Models

To compare the information gain introduced by incorporating race and cost-consciousness indicators in the campus micromobility model, we analyzed the model's goodness-of-fit statistics and calculated a series of likelihood ratio tests (as shown in **Table 6**). These comparisons are based on the model's adjusted Rho-Squared to balance the differences in the number of parameters. Based on these results, each extension of Model A improved the goodness-of-fit.

According to these statistics and considering the chi-square (χ^2) distribution with corresponding degrees of freedom, Models B, C, and D show statistically significant improvements over Model A. Furthermore, Model D demonstrates significant superiority over Models B and C, which individually incorporate only racial or cost consciousness variables. These findings suggest that the sequential model expansion from Model A to Model D significantly enhances the explanatory power for transportation mode choice behavior.

Table 6: Likelihood-ratio Test for the four Models

Models compared	LR[1]	P-value	Df[2]
B vs. A	79.43	<0.001	4
C vs. A	18.13	0.797	24
D vs. A	94.884	<0.001	28
D vs. B	15.454	0.907	24
D vs. C	76.754	<0.001	4

1. *LR* = Chi-Squared likelihood ratio test statistic: $-2*[LL_{alt} - LL_{base}]$.
2. *df* = degrees of freedom for the $\chi 2$ statistic defined as the difference.

While the improvements in some models after incorporating racial variables were not statistically significant (P-value > 0.05), this does not mean that race has no potential impact on mode of transportation choice. Certain trends can still be observed from the model results: for example, East Asian and Southeast Asian populations are more likely to choose e-scooters, while their white counterparts prefer driving. Although these trends did not reach statistical significance, it is still necessary to design more targeted transportation policies for different racial groups in practical applications. This will help to consider the travel needs of different groups more comprehensively and achieve more inclusive and equitable transportation planning.

4.4 Impact of Establishing e-Scooter Parking Zones

4.4.1 Impact of e-Scooter Parking Zones on Campus Micromobility Model Estimation Results

Based on the composite model from the previous section, we conducted a comparative analysis of the impact of establishing dedicated e-scooter parking zones on travel mode choice, as shown in **Table 7**. This analysis involves two scenarios: Scenario 1 (without e-scooter parking zones) and Scenario 2 (with e-scooter parking zones), focusing on comparing the travel mode preferences, time and cost sensitivity, and the impact of individual characteristics on transportation choices for different groups in these two scenarios. Additionally, the model incorporates individual-level cost awareness and racial-ethnic group preferences for travel mode choices.

Table 7: E-scooter Parking Area Impact on Mode Choice Parameters

			Scenario 1	Scenario 2
Variables		Travel Modes	Non-designated e-Scooters Parking Area	Non-designated e-Scooters Parking Area
Alternative Specific Constant	ASC_Walk		1.053 (1.975)	1.023 (2.723)
	ASC_Bike		NA	NA
	ASC_e-Scooter		1.848 (3.579)	1.457 (4.108)
	ASC_Drive		1.177 (1.986)	1.072 (3.045)
Travel Scenario				
	Travel Time		-0.022 (-3.537)	-0.012 (-3.001)
	Walk Time		-0.034 (-2.944)	-0.036 (-4.085)
	Travel Cost		-0.016 (-2.018)	-0.014 (-3.342)
	e-Scooter Dependency		-1.957 (-9.879)	-1.048 (-6.608)
Individual level characteristics				
Cost Conscious	High Cost Conscious	Walk	1.501 (6.542)	0.328 (2.622)
		Bike	0.554 (1.982)	-0.207 (-1.832)
	Low Cost Conscious	e-Scooter	1.328 (2.273)	-0.556 (-4.184)
		Drive	1.418 (3.363)	0.664 (4.217)
Ethno-racial Groups	Black African Descent	Walk	0.59 (2.235)	0.346 (1.908)
		Bike	-7.444 (-4.165)	-2.927 (-4.199)
		e-Scooter	-	0.804 (5.305)
		Drive	-	-3.375 (-5.98)
	East Asian	Walk	-	-0.264 (-2.578)
		Bike	0.844 (1.958)	0.23 (2.121)
		e-Scooter	0.397 (2.195)	-
		Drive	-0.584 (-2.977)	-
	White	Walk	-	-
		Bike	-	-
		e-Scooter	-0.484 (-2.671)	-0.266 (-2.42)
		Drive	0.372 (2.287)	0.171 (1.884)
	Hispanic Non-White	Walk	-	-
		Bike	-	-
		e-Scooter	-	-
		Drive	-0.525 (-2.224)	0.209 (1.769)
	Hispanic White	Walk	-	0.354 (2.398)
		Bike	-9.685 (-2.893)	-3.046 (-3.997)
		e-Scooter	-	-0.263 (-2.349)
		Drive	-	0.211 (1.838)
	Southeast Asian	Walk	-0.621 (-3.864)	0.252 (1.848)
		Bike	0.914 (3.039)	-
		e-Scooter	0.465 (2.174)	-
		Drive	-	-
Other				
Nest Scales (μ)	Motorized Modes		2.798 (5.257)	2.401 (4.127)
	Active Modes		1.270 (2.885)	3.009 (3.462)
	Time Value ($/hr)		43.64	70.00
Number of observations (N)			1368	1326
Null log-likelihood (L(0))			-1896.451	-1838.226
Model log-likelihood (L(b))			-1373.568	-1343.849
Rho-squared			0.276	0.269
Adjusted rho-squared			0.267	0.26

Note: t-statistic in parentheses; NA = not applicable; “—" = coefficients are insignificant at 90% confidence interval

Model estimation results show that the establishment of e-scooter parking areas has a significant impact on campus micromobility behavior. Changes in the alternative specific constants reflect the impact of parking area setup on the basic utility of various modes of transportation. The basic utility of Walk, e-Scooter, and Drive all increased, decreasing from 1.053, 1.848, and 1.177 to 1.023, 1.457, and 1.072, respectively. This widespread reduction in utility suggests that standardized parking facilities may alter people's basic perceptions of various modes of transportation. It is particularly noteworthy that after the establishment of parking areas, the negative effect of shared e-scooters was significantly weakened, with the coefficient increasing from -1.957 to -1.048. This change indicates that the establishment of parking areas effectively improves people's acceptance of shared e-scooters. Standardized parking facilities not only improve street order but also enhance users' confidence in using shared micro-mobility systems (James et al., 2019). Dedicated parking areas effectively alleviate users' parking anxiety, thereby increasing their willingness to use shared e-scooters (A. Brown et al., 2020).

After the establishment of e-scooter parking areas, the travel time coefficient decreased from -0.022 to -0.012, indicating that standardized e-scooter parking facilities reduced the time sensitivity of travelers. At the same time, cost sensitivity also decreased slightly, with the coefficient changing from -0.016 to -0.014. Although this change is small, it is still statistically significant. The value of time increased significantly from $43.64/hour to $70/hour, indicating that when the infrastructure of shared e-scooter systems is improved and effectively integrated with public transportation systems, users are more concerned with travel convenience rather than simply travel time and transportation costs (Fearnley et al., 2020). Fixed parking locations reduce the uncertainty of finding parking spaces, thus reducing travelers' concerns about time when planning their trips.

In terms of socioeconomic characteristics, the impact of parking area settings on different groups shows significant differences. The preference for walking among high-cost-conscious groups decreased significantly, with the coefficient decreasing from 1.501 to 0.328, and their attitude towards bicycles even changed from positive (0.554) to negative (-0.207). Similarly, the preference for e-scooters among low-cost-conscious groups also changed from positive (1.328) to negative (-0.556). This significant shift in preference reflects the complex impact of standardized parking facilities. Jafarzadehfadaki and Sisiopiku (2024) found in a comparative study of Washington, D.C., Miami, and Los Angeles that while improvements in micromobility infrastructure have improved management efficiency, fixed parking areas may reduce flexibility of use, thereby affecting the willingness of different groups to use them. These findings suggest that the improvement of parking facilities may fundamentally change people's evaluation criteria for modes of transportation, making travel choices that were originally based on cost considerations more complex.

The transportation choice behavior of racial groups has also changed significantly. The attitude of African Americans towards e-scooters has shifted from no significant preference to a strong positive preference (0.804); the preference coefficients of East Asians for various modes of transportation have generally decreased; the preference for private cars among white people has weakened (from 0.372 to 0.171); while the attitude of Southeast Asians towards walking has shifted from negative preference (-0.621) to weak positive preference

(0.252). This trend is consistent with the findings of Jafarzadehfadaki and Sisiopiku (2024) in three major cities, who pointed out that there are significant differences in the acceptance and usage patterns of micromobility facilities among different racial groups. Bozzi and Aguilera (2021) further suggest that improvements in micromobility infrastructure have a differentiated impact on groups with different cultural backgrounds, an impact that is not only reflected in usage frequency but also leads to a restructuring of their overall travel patterns. These findings highlight the importance of considering a multicultural perspective when planning micromobility facilities.

These findings have important policy implications for campus micromobility planning. The setting of parking areas not only affects people's actual usage behavior but also changes the basic understanding and preferences of different groups for various modes of transportation. The complexity and multidimensionality of this impact suggest that when promoting the construction of micromobility facilities, it is necessary to fully consider the needs and behavioral characteristics of different groups and adopt more targeted planning strategies.

4.4.2 Changes in Mode Choice Probabilities After Designing e-scooter Parking Areas

Table 8: Modal Share Changes After e-Scooter Parking Implementation

	P_Walk	P_Bike	P_eScooter	P_Drive
True Probability	42.79%	7.96%	23.88%	25.37%
Scenario 1	46.33%	10.05%	24.69%	18.93%
Scenario 2	45.24%	13.38%	20.10%	21.28%

Table 8 demonstrates the significant impact of e-scooter parking zone implementation on

campus transportation mode choice probabilities. Empirical analysis reveals systematic changes in users' travel choices following the establishment of dedicated parking areas. The predicted walking probability decreased from 46.33% (without dedicated parking) to 45.24%, with a reduced deviation from the observed value (42.79%), indicating that Scenario 2 better captures the influence of infrastructure improvements on pedestrian.

However, e-scooter usage patterns exhibited unexpected changes. The predicted utilization rate decreased from 24.69% to 20.10%, falling below both Scenario 1's prediction and the observed value (23.88%). This counter-intuitive result reveals an important phenomenon: while dedicated parking zones reduced the time cost of finding parking spaces through standardized parking behavior, the fixed parking locations may have diminished usage flexibility, thereby affecting user preferences.

Regarding motorized transportation, the probability of choosing private vehicles increased from 18.93% to 21.28%, gradually approaching the observed value (25.37%), a trend that aligns with UCLA's unique spatial layout characteristics. The implementation of dedicated parking zones enhanced e-scooters' function as a "last-mile" connection solution for motorized travel, providing more efficient connectivity between parking facilities and academic areas.

Notable changes were observed in bicycle usage rates. The predicted value increased from 10.05% to 13.38%, widening the deviation from the observed value (7.96%). This phenomenon suggests that when e-scooter usage becomes constrained by fixed parking locations, some users may shift to bicycles as an alternative for short-distance travel, although the model may overestimate the magnitude of this substitution effect.

These findings have important implications for policy evaluation. When assessing the potential impact of new policy measures, a more systematic approach is needed to examine user behavioral adjustment mechanisms and improve the model framework to more accurately capture the complex systemic effects of infrastructure changes. Specifically, a staged prediction strategy could be adopted to reduce uncertainty accumulation in long-term forecasting, while introducing more refined control variables to enhance the model's predictive capability for post-intervention behavioral changes.

5. Discussion and Conclusion

5.1 Key Findings

As transportation planners and policymakers increasingly recognize the potential of micromobility options such as e-scooters in promoting sustainable urban mobility and enhancing transportation equity, our analysis of mode choice behavior provides important insights into how sociodemographic characteristics, attitudinal factors, and infrastructure policies influence micromobility adoption across different urban contexts.

This study employs a mixed-method approach, combining descriptive statistics and travel scenario modeling to systematically investigate the multidimensional factors influencing users' transportation choice behavior. Compared to existing research, the innovation of this study lies in constructing a more comprehensive demographic characteristic framework, which not only examines basic dimensions such as gender and race but also pays special attention to educational status as a key variable in the campus context, while incorporating subjective preference factors such as cost consciousness and environmental awareness into the analysis. The research findings indicate that the composite Model D, which integrates variables such as race and cost consciousness, significantly enhanced the explanatory power for campus micromobility preferences, demonstrating not only better overall goodness of fit but also capturing subtle differences in user preferences, thus providing richer and deeper insights into understanding campus micromobility choice behavior.

The research reveals that users' demographic characteristics significantly influence their transportation choices. Gender differences are notable, with males showing higher usage rates of e-scooters than females and demonstrating a greater inclination to try innovative transportation modes. The differences in educational status are particularly evident: undergraduate students exhibit significantly higher e-scooter usage rates than graduate students, a disparity that may stem from differences in residential location (Fearnley et al., 2020). With 67.5% of undergraduate students living on campus compared to 86.4% of graduate students residing off campus, the proximity of residence to campus directly influences their transportation choices.

At the socioeconomic level, our research findings both align with and differ from existing literature regarding e-scooter user characteristics. We found that environmentally conscious individuals are more likely to use e-scooters, which echoes the findings of Shaheen and Cohen (2020). However, our study reveals unique patterns in the relationship between income and usage rates. While existing literature typically suggests higher e-scooter usage among high-income groups (Jafarzadehfadaki & Sisiopiku, 2024), our study shows that low-income users also demonstrate significant usage rates, comparable to their driving rates. These findings suggest that e-scooter user characteristics in campus environments may differ from those in general urban settings, emphasizing the need for context-specific understanding of micromobility adoption patterns.

The impact of cost consciousness, similar to our findings about income levels, further reveals the core role of economic factors in individual travel decisions. While both high and low-income groups showed significant e-scooter adoption rates, cost-conscious individuals demonstrated distinct travel patterns regardless of their income level. In some specific travel scenarios, such as daily commuting to school or work, individuals often need to make trade-offs between convenience and economy. Therefore, this differentiated analysis of cost consciousness not only provides insights into individual choices but also provides a basis for formulating differentiated policy measures. For example, increasing the availability of shared micromobility or reducing the cost of using shared e-scooters may effectively guide different types of users to make more environmentally friendly and economical choices.

Introducing the impact of racial characteristics on transportation choice behavior helps to reveal the sociocultural factors behind mode choice. These factors can have a profound impact on the travel experience of specific groups, so it is necessary to fully consider these sociocultural contexts in transportation planning and policy making to ensure the fair allocation and effective utilization of transportation resources. For example, in campus areas that primarily serve diverse populations, policies tailored to the specific needs of different groups, such as increasing the promotion of shared scooters or improving bicycle facilities, can effectively improve the inclusiveness and service level of the transportation system.

The impact analysis of parking zone implementation reveals systematic changes brought by infrastructure improvements. The most significant change is the reduced sensitivity to user travel time, with the value of time increasing from \$43.64/hour to \$70.00/hour. Different groups show varying responses to facility improvements, suggesting that infrastructure improvements reshape users' travel decision mechanisms. Establishing dedicated e-scooter parking areas can increase shared e-scooter usage (Bai & Jiao, 2020; James et al., 2019).

These comprehensive findings not only deepen our understanding of campus micromobility usage patterns but also provide important guidance for future transportation planning. The research indicates that successful micromobility systems need to simultaneously consider demographic characteristics, socioeconomic factors, attitudinal tendencies, and infrastructure conditions. Only by adopting such a multidimensional, comprehensive approach can truly effective and inclusive transportation policies be formulated.

5.2 Policy Recommendations

Based on the findings, we recommend that campus micromobility policies adopt differentiated, inclusive, and systematic strategies. Given the significant differences in user demands for e-scooter infrastructure across different groups, infrastructure planning should fully reflect the actual needs of users. As emphasized by Smith (2022) in the Vision Zero plan, systematic integration of transportation is critical for improving overall travel efficiency.

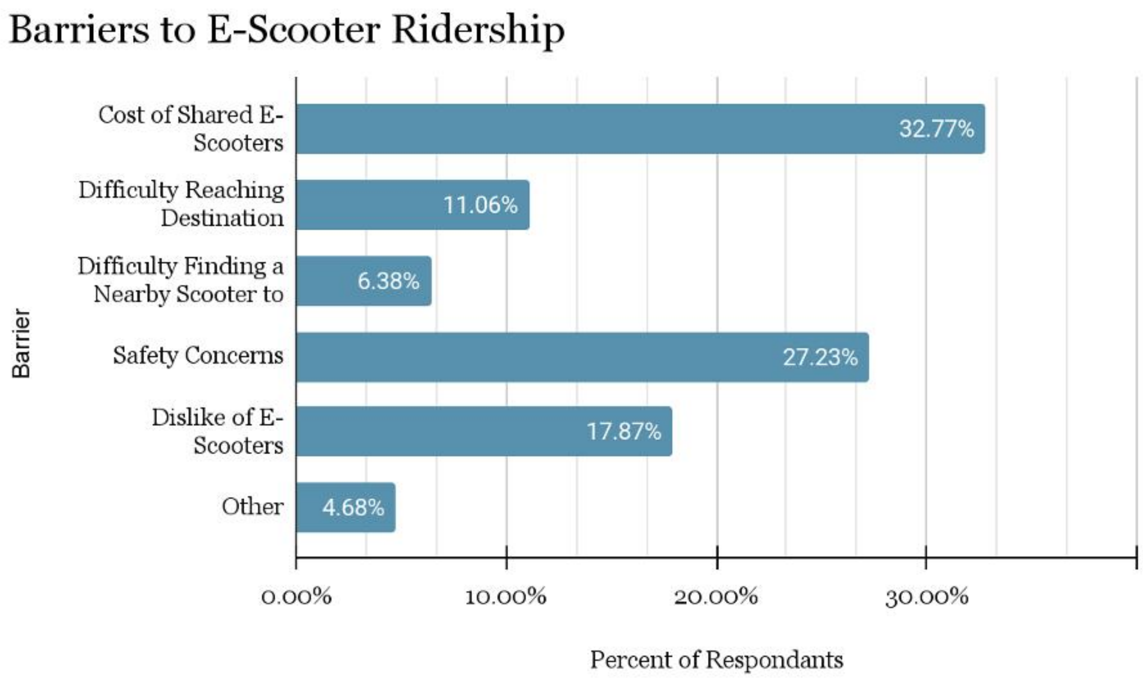


Figure 11: Barriers to E-Scooter Ridership

The **Figure 11** highlights that the high cost of shared e-scooters (32.77%) and safety concerns (27.23%) are the primary barriers to ridership. Addressing cost concerns, we recommend providing subsidies or discounts to low-income users (representing 33.3% of respondents) and implementing flexible pricing strategies to better serve cost-sensitive groups. To mitigate safety concerns, infrastructure improvements and targeted safety education programs are essential. Notably, safety initiatives tailored for female users should be prioritized to address the specific needs identified in the study.

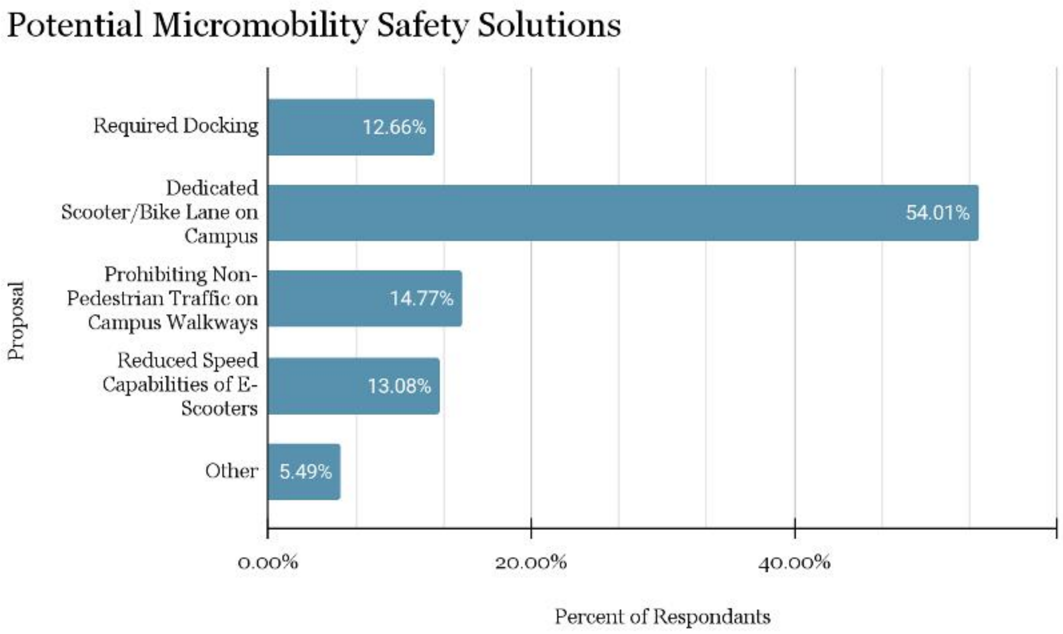


Figure 12: Potential Micromobility Safety Solutions

Regarding infrastructure development, the **Figure 12** reveals that the addition of dedicated scooter/bike lanes on campus is the most widely supported measure (54.01%). We therefore recommend prioritizing the construction of such lanes, especially those connecting dormitories, academic areas, and public transit hubs. Furthermore, strategically increasing the number of e-scooter parking facilities in undergraduate-dominated areas, such as near dormitories, and integrating clear directional signage systems will enhance user experience and promote compliance with parking regulations.

Modern technology should also be leveraged to enhance management efficiency. The establishment of a smart management platform could enable real-time monitoring of parking zone usage, optimize vehicle allocation and maintenance schedules, and improve user-friendly reservation and payment systems. Enhanced parking management, such as the clarification of usage rules and continuous service quality improvements, is particularly critical for ensuring operational effectiveness and user satisfaction.

Given the significant influence of racial and economic factors on transportation choices, micromobility policies must promote social equity. For instance, multilingual service interfaces and promotional materials should be developed to accommodate diverse racial groups, thereby improving accessibility and awareness. Subsidy programs should be designed to ensure equitable access for low-income populations. Additionally, dedicated educational initiatives targeting female users could further enhance their confidence and safety when using micromobility options.

The comprehensive implementation of these measures will help establish a more inclusive, efficient, and sustainable campus transportation system. By holistically addressing demographic characteristics, socioeconomic factors, and infrastructure conditions, these recommendations aim to significantly improve the quality of campus micromobility services and better meet the travel needs of diverse user groups. As these policies are implemented and continuously refined, the campus transportation system will evolve into a more comprehensive and inclusive service framework.

5.3 Research Limitations and Future Directions

This study has several noteworthy limitations. First, in the transportation mode choice modeling process, we were unable to include the public transit system. This is because public transit involves many unique factors, such as number of transfers, waiting time, and carriage crowding levels, which fundamentally differ from other transportation modes' characteristics and are difficult to analyze uniformly under the existing model framework. While this simplification improves model comparability, it also somewhat limits the study's understanding of the overall campus transportation system. Furthermore, this study's sample size (243 valid questionnaires) is relatively limited, with some groups particularly underrepresented. For example, in racial analysis, the sample sizes for African Americans (14 people) and Hispanic/Latinx (white) (20 people) are small, which may affect the representativeness and reliability of related analysis results. Additionally, samples mainly concentrate on data collection during specific periods, potentially not fully reflecting travel pattern changes throughout the academic year.

Based on these limitations, we suggest that future research needs to develop more complex model frameworks, such as Joint models, to integrate public transit as an important transportation mode. This requires incorporating more dimensional variables into the model, such as transfer convenience, waiting time, and carriage crowding levels, to more comprehensively reflect public transit travel characteristics. Meanwhile, the model also needs to consider the interactive effects between these factors and other transportation mode choices. Second, future research should expand the range of considered factors to incorporate environmental variables into the analysis framework. For example, weather conditions (such as precipitation, temperature) and topographical features may significantly influence travelers' transportation mode choices. The interaction between these natural environmental factors and existing socioeconomic variables may reveal richer travel behavior patterns.

Furthermore, with the large-scale deployment of Veo brand shared e-bicycles around UCLA campus beginning in Fall 2024, future research needs to incorporate this emerging micromobility mode. This involves not only analyzing usage patterns of the new transportation mode but also studying its competitive and complementary relationships with existing e-scooter systems, as well as its impact on the overall campus transportation landscape.

Future research will conduct larger-scale, longer-term data collection, both expanding sample size to improve research representativeness and conducting longitudinal tracking studies to capture dynamic changes in travel behavior. Particularly in the context of continuous introduction of new transportation modes, continuous observation and analysis are especially important for understanding campus transportation system evolution trends. These improvements will help build more comprehensive and accurate campus transportation behavior models, providing more reliable theoretical foundations for future policymaking. Meanwhile, these studies may also provide valuable references for other similar campus environments.

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