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Investigating the role of shared e-scooters in First Mile Last Mile transportation for different income groups

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Abstract

Shared Electric Scooters (E-Scooters), characterised by small, lightweight vehicles, and electric powered, are rapidly gaining popularity in Malaysia as a sustainable and efficient transportation solution. Shared E-scooters have seen significant growth, with a 65% increase in users and a 2.5-fold rise in trips in 2022. Current studies indicate that e-scooter users are predominantly younger, well-educated, and male, with higher-income individuals often being early adopters. Moreover, previous studies suggested that e-scooters have emerged as a popular First Mile Last Mile (FMLM) transport option due to their flexibility, cost-effectiveness, and environmental benefits. However, the usage patterns among lower-income groups remain underexplored, raising questions about the inclusivity of e-scooter services. This study aims to bridge the gap in research regarding the relationship between e-scooter usage for FMLM and its associated factors, focusing on the unique dynamics of the Klang Valley. A Stated Preference (SP) was conducted to collect information regarding respondents' preferences for First Mile Last Mile (FMLM) travel modes and the associated socio-economic factors influencing it. Four mode choice scenarios using various transport modes (e.g., E-hailing, E-scooter, walking and Rapid Bus) were presented to respondents. Using E-scooter as a reference mode choice, the results of logistic regression analysis revealed that travel time significantly affects choices for E-Hailing, Walking, and Rapid Bus. Travel costs notably influence E-Hailing choices. The findings could shed light on improving transport planning and management related to e-scooters, which hold substantial promise in shaping the future of public transportation in Malaysia, serving as an affordable and convenient "First Mile Last Mile" solution for commuters.

1 Introduction

Micromobility is a rapidly growing phenomenon in Malaysia, with a notable surge in popularity, especially in the realm of public transportation. This trend centres around the utilization of small and lightweight vehicles, which can be either human-powered or electric, to facilitate short-distance journeys. These vehicles are often privately owned or accessible through rental services, making them versatile options for navigating urban environments (Fitt & Curl, 2020). The key objectives of micromobility are twofold: firstly, to provide a sustainable alternative to conventional car trips for short distances, thereby contributing to reduced emissions and congestion in crowded urban areas (Zagorskas & Burinskienė, 2020). Secondly, and just as importantly, micromobility plays a vital role as the "first mile" and "last mile" solution for public transportation networks (Giuffrida et al., 2020). By providing accessible, convenient, and eco-friendly transportation options that seamlessly connect commuters to and from public transit hubs, micromobility enhances the overall efficiency and accessibility of public transport systems, fostering a more sustainable and interconnected urban landscape.

In Malaysia, shared electric scooters have emerged as a prominent player in the realm of micromobility, alongside shared bikes, and these services are offered by various micromobility companies, including Beam, a Singapore-based micromobility firm. The utilization of electric scooters has witnessed a consistent upsurge, as indicated by Beam's 2022 report, demonstrating a remarkable 65% increase in new users and a 2.5-fold rise in the number of

trips conducted in comparison to the preceding year (Beam Malaysia, 2023). Moreover, the Malaysian government has recognized the potential of electric scooters in addressing transportation challenges, exemplified by the initiation of a sandbox project in Shah Alam under the purview of the Town and Country Planning Department, PLANMalaysia (Guidelines on Micromobility Vehicle Route Plan finalised). This underscores the government's proactive approach in fostering innovative solutions to enhance urban mobility. Furthermore, the idea of electric scooters serving as a "first mile" transport option has garnered substantial support, with 57.3% of respondents expressing their endorsement of the concept, emphasizing its potential to alleviate traffic congestion in the bustling Klang Valley (Ikeh & Yuen, 2022). Collectively, these developments underscore the significant potential of electric scooters in shaping the future of public transportation in Malaysia. They offer an affordable and convenient "First Mile Last Mile" (FMLM) alternative for commuters, thereby addressing critical transportation needs in a rapidly evolving urban landscape.

E-scooters have emerged as a popular First Mile Last Mile (FMLM) transport option due to their flexibility, cost-effectiveness, and environmental benefits. They are particularly effective in bridging the gap between traditional public transport systems and final destinations. Despite their growing popularity, there is a lack of comprehensive research on how various factors such as education, occupation, income, and gender influence e-scooter adoption. Current studies indicate that e-scooter users are predominantly younger, well-educated, and male, with higher-income individuals often being early adopters (Cao et al., 2021).

However, the usage patterns among lower-income groups remain underexplored, raising questions about the inclusivity of e-scooter services. While e-scooters could offer an affordable transportation option for low-income individuals, challenges such as safety concerns, lack of dedicated infrastructure, and limited access may impede their widespread adoption. Studies from different regions show varied relationships between income and e-scooter usage; for example, research in Texas suggests lower usage among higher-income groups, while findings from Portland indicate the opposite (Jiao & Bai, 2020; Caspi, Smart, & Noland, 2020). This inconsistency highlights the need for context-specific studies to understand the relationship between the users' income and their usage of e-scooter.

In the Klang Valley, a diverse and densely populated urban area in Malaysia, understanding the dynamics of e-scooter adoption is crucial for developing inclusive and effective urban mobility strategies. This study aims to fill the research gaps by examining how income levels influence e-scooter usage, particularly focusing on the underrepresented low-income B40 group. By exploring these factors, the research seeks to provide insights into how e-scooters can be better integrated into the urban transport ecosystem, ensuring they serve as a sustainable and inclusive mobility solution.

2 Literature review

The exploration of shared electric scooters as a First Mile Last Mile (FMLM) transportation solution has gained increasing attention as cities worldwide pursue sustainable and efficient transit alternatives. Understanding the potential and market opportunities of this mode of transportation is essential. Furthermore, grasping the preferences of e-scooter users for FMLM transport is pivotal for shaping transformative policies that can influence urban transportation systems. Recent studies have highlighted the evolving role of e-scooters in urban mobility, emphasizing their potential to address FMLM challenges (Sanders, Branion-Calles, & Nelson, 2020).

Intriguingly, research has revealed contradictions between the stated preferences of low-income individuals and their actual e-scooter usage patterns. While these individuals may express a preference for e-scooters as an affordable transportation option, actual usage can be constrained by local conditions, infrastructure, and other barriers (James et al., 2019). This discrepancy underscores the need to consider regional differences and local factors when

analyzing e-scooter adoption, rather than assuming uniform usage patterns across various regions.

The exploration of shared electric scooters as a First Mile Last Mile (FMLM) transportation solution has emerged as an increasingly vital area of research, as cities worldwide seek sustainable and efficient transit alternatives. The first crucial step involves grasping the potential and market opportunities that this mode of transportation presents. Furthermore, comprehending the preferences of e-scooter users for FMLM transport is pivotal before the implementation of transformative policies that can shape the urban transportation landscape. To gain insights into these preferences, two fundamental approaches can be employed: stated preference and revealed preference. In this context, the former proves particularly valuable, offering a comprehensive understanding of user inclinations and expectations.

Recent studies have revealed intriguing contradictions between the stated preferences of low-income individuals and their actual e-scooter usage patterns. While these individuals may express a preference for e-scooters as a cost-effective mode of transportation, their actual usage may be hindered by local conditions, infrastructure, and other barriers. This highlights the importance of considering regional differences and local factors when analysing e-scooter adoption, rather than assuming uniform usage patterns across different jurisdictions and global boundaries. This discrepancy forms a noteworthy area of investigation within this research, delving into the underlying factors and relationships that contribute to this apparent paradox. By scrutinizing these dynamics, the study seeks to unravel the nuanced decision-making processes that influence the low-income demographic's interaction with e- scooters. Ultimately, this research endeavours to inform the development of effective policies and strategies to promote the integration of e-scooters into the broader urban transportation ecosystem, aligning the offerings with the preferences and needs of low-income commuters and enhancing the overall sustainability and accessibility of FMLM transport solutions.

2.1 Opportunities as a FMLM

The expansion of shared e-scooter services has introduced a growing paradigm shift in the transportation landscape, yet research concerning the utility of e-scooters as a First Mile Last Mile (FMLM) transport mode remains notably limited. Examining reports from Malaysia, particularly in the bustling Klang Valley, a survey assessing commuter perspectives on whether e-scooters can mitigate first-mile traffic congestion reveals a split consensus, with 58% in agreement and 42% in disagreement. This dynamic suggests that shared e- scooters bear the potential to alleviate traffic congestion if consistently embraced (Ikeh & Yuen, 2022). However, the existing research primarily centres on user preferences without delving into the multifaceted factors influencing these choices, necessitating in-depth investigations to substantiate these findings.

Further insights can be gleaned from studies in Chicago, where e-scooters are projected to enhance the accessibility of FMLM options, potentially expediting 24% to 29% of transit journeys (Smith, 2020). In the same locale, it has been demonstrated that e-scooters effectively cater to short trips within half-mile to two-mile radii and effectively bridge transportation gaps within neighbourhoods by complementing existing transit and bikeshare systems (Smith & Schwieterman, 2018). Meanwhile, investigations conducted across North America have indicated that a notable percentage of e-scooter users, ranging from 5% to 70% contingent upon the contextual nuances of the study, have leveraged e-scooters as an integral component of their FMLM transport strategies (Wong, 2023).

These collective studies illuminate the vast potential of e-scooters as a viable FMLM transport solution. Consequently, this research aims to explore the underlying factors and motivations that drive the increased adoption of e-scooters in this pivotal role. By scrutinizing these aspects, the study seeks to unravel the intricate dynamics influencing the integration of e-scooters into urban transportation and FMLM strategies. This understanding, in turn, can

contribute to the formulation of effective policies that align with the evolving preferences and needs of commuters, facilitating the seamless and sustainable integration of e-scooters into the broader urban transportation framework.

2.2 Understanding E-Scooter Usage and Demographic Preferences

The adoption of shared e-scooters varies significantly across different demographic groups, influenced by factors such as age, gender, income, and education. Studies consistently show that younger individuals are more likely to use e-scooters. In Austin, Texas, data indicates that a large proportion of e-scooter users are under the age of 34, with significant usage among individuals aged 18-24 (Jiao & Bai, 2020). Similarly, research from Singapore demonstrates a strong preference for e-scooters among young, high-income males, driven by factors such as convenience, tech-savviness, and lifestyle choices (Cao et al., 2021).

Gender differences also play a significant role in e-scooter usage. For instance, in Washington, DC, data shows a higher proportion of male e-scooter users compared to females. This pattern is consistent with findings from Austin, Texas, where men are more likely to use e-scooters, potentially due to a greater willingness to adopt new technologies and lower perceived safety concerns (Jiao & Bai, 2020;McKenzie, 2019).

Income also significantly influences e-scooter usage patterns. In Los Angeles, research indicates that higher-income individuals are more likely to use e-scooters, reflecting their ability to afford the costs associated with frequent usage and access to areas where e-scooter infrastructure is well-developed (Yan et al., 2023). Similarly, in Washington, DC, e-scooter usage is more prevalent in affluent neighborhoods with better infrastructure and amenities (McKenzie, 2019). These findings suggest that while e-scooters are accessible to a wide range of income levels, their usage is concentrated among those who can afford it and live in areas with supportive infrastructure.

Educational attainment is another key factor influencing e-scooter usage. Studies indicate that individuals with higher levels of education are more likely to use e-scooters, potentially due to greater environmental awareness and a preference for sustainable transportation options. For example, data from Singapore highlights that higher education levels are associated with increased e-scooter usage, reflecting a trend towards environmentally conscious mobility choices among the educated population (Guo & Zhang, 2021).

2.3 Contradictions between low income and e-scooter usage

The relationship between income and e-scooter usage is complex, with conflicting evidence from various studies. Research conducted in Austin, Texas, found that individuals with lower incomes are more likely to use e-scooters, indicating that these vehicles serve as a cost-effective transportation option for those who may not have access to private cars or find public transport options less convenient (Jiao & Bai, 2020). This finding is supported by data showing high e-scooter usage in areas with lower median household incomes, suggesting that e-scooters fulfil an important mobility need for economically disadvantaged groups (Jiao & Bai, 2020).

Contrastingly, studies from other regions present different outcomes. For instance, in Portland, research reveals that e-scooter usage is lower in low-income neighborhoods, despite the potential cost advantages. This could be due to factors such as limited access to e-scooter services, higher levels of safety concerns, or the lack of supporting infrastructure in these areas (Caspi, Smart, & Noland, 2020). Similarly, in Washington, DC, and Los Angeles, higher e-scooter usage is observed in wealthier areas, suggesting that income correlates positively with e-scooter adoption in these cities. This discrepancy points to the influence of local context, infrastructure, and the availability of services (McKenzie, 2019; Yan et al., 2023).

Further evidence from Paris indicates that the integration of e-scooters into the urban transport network is more successful in areas with higher incomes, where residents are more likely to adopt e-scooters as a convenient and modern mode of transportation. The availability of infrastructure, such as bike lanes and parking spaces, plays a significant role in supporting e-scooter usage in these areas, making them more accessible to higher-income individuals (Latinopoulos, Patrier, & Sivakumar, 2021).

These contrasting findings emphasize the need for targeted research to fully understand the relationship between income and e-scooter usage. In Malaysia, understanding these dynamics is crucial for developing policies that can promote e-scooter usage across all income levels. By addressing barriers such as cost, safety, and infrastructure, policymakers can create a more inclusive and effective transportation system that leverages the benefits of e-scooters for diverse demographic groups. This approach is essential to optimize the role of e-scooters as a First Mile Last Mile (FMLM) transportation mode, ensuring equitable access and usage across different income segments.

3 Methodology

3.1 Stated Preference Experiments Design

In pursuit of this research, a comprehensive quantitative survey approach was employed to delve into users' perspectives and perceptions of e-scooters. Drawing inspiration from a Stated Preference (SP) experiment carried out in five diverse European cities (Esztergár-Kiss et al., 2022), this study aimed to capture a broad range of data. The core objective of the survey questionnaire was to gain a thorough understanding of users' needs and prerequisites regarding the utilization of e-scooters as a First Mile Last Mile (FMLM) transport mode.

The survey instrument was meticulously designed, incorporating a mix of multiple-choice and Likert-type scale questions. These questions were crafted based on established guidelines for stated preference analysis (Hensher, 1994), ensuring the reliability and validity of the collected data. Multiple-choice questions covered demographic information, current travel behaviors, and preferences for various travel modes, while Likert-type scale questions assessed attitudes and perceptions towards e-scooter usage under different scenarios. Furthermore, the survey included hypothetical scenarios to understand how different factors, such as cost, travel time, and safety measures, influence e-scooter adoption. This multifaceted approach allowed for a detailed analysis of the factors driving e-scooter use and preferences among urban commuters.

The SP survey was designed to be more than a tool for academic inquiry; it was also intended to offer practical insights to e-scooter operators. By analyzing user responses, the research aimed to identify specific areas where service improvements could be made, such as enhancing safety features, optimizing pricing strategies, and improving accessibility. These insights can help operators tailor their services to better meet the evolving needs and preferences of users. Moreover, the findings from this survey are expected to inform policymakers and urban planners. By understanding the factors that influence e-scooter adoption and usage, stakeholders can develop targeted strategies to promote sustainable urban transportation. This includes creating safer infrastructure for e-scooters, integrating e-scooters into public transportation networks, and implementing policies that encourage their use as a viable FMLM solution.

In summary, this research employs a detailed and methodologically robust survey approach to uncover the dynamics of e-scooter usage. The insights gained are poised to benefit both e-scooter operators and urban transportation planners, ultimately contributing to the development of more user-centered and sustainable urban mobility solutions.

3.2 Model development

In the process of handling the data collected through the Stated Preference (SP) analysis, meticulous attention is devoted to the unique characteristics of this dataset, with a paramount aim of extracting optimal results. An intrinsic consideration in this endeavour is the potential for inaccuracies stemming from behavioural inconsistencies and biased responses among individuals, which can introduce noise into the decision-making information. To circumvent these challenges, the research approach prioritizes user preferences over rigid, deterministic responses, adopting a probabilistic modelling framework. Specifically, for this research, the Multinomial Logit Model (MNL) devised by Koppelman and Bhat is chosen due to its suitability for experiments involving a limited set of alternatives (Koppelman & Bhat, 2006).

The research process is modelled in alignment with the experimental framework conducted across five European cities, aiming to assess the travel behaviour of e-scooter users through stated preference experiments (Esztergár-Kiss et al., 2022). This approach seeks to leverage the insights and findings of this preceding research to refine and enrich the understanding of e-scooter users' preferences and behaviours within the specific context of the research's objectives, contributing to the development of robust models and actionable insights for e-scooter operators and policymakers. The aim is to develop robust models that provide actionable insights into how income levels influence e-scooter usage for First Mile Last Mile transport. This involves examining travel behavior patterns among different income groups to understand barriers and motivators for e-scooter adoption

$$Ui = Vi + \varepsilon i \quad (1)$$

The MNL model first consisted of the utility function that reflects the value of an alternative based on its preference and characteristic.

In which the Ui represents the utility of the alternative, Vi is the established component of the utility and εi is the error parameter of the alternative. Moving on, the model would continue to the logit expression that probability condition.

For the systematic function consists of an alternative specific constant (ASC), the summation of all attributes of an alternative and the specific characteristic of the respondent.

$$Vii = ASCi + \sum k\ \gamma Ak,i + \sum m\ \beta i,m \quad (2)$$

The main part of the expression is the weighted sum of the attribute levels βm of alternative i, and the portion of utility associated with the characteristics Ak of the respondents, with γ and β being their respective coefficients. The importance of independent variables m (fares, travel time) and the respondent's characteristics k (income) for each utility of the alternative. The ASC is the respondents' estimated average preference for alternative I respective to the set of reference alternatives.

The modelling result would depend on the model parameters, which are the income, age and gender that are selected to characterize the respondent in each utility function. The models imply the dependence of the preferences on these parameters. Thus the utility function for each alternative is a function of its attribute levels of fare and travel time, with the respondent's characteristic made up by income. The equation considers that income parameter along with its appended coefficient γi. For each alternative, the utility value of time and fare is equal.

3.3 Survey design

The survey is structured into three distinct sections, each designed to gather comprehensive information about the respondents. Section 1 focuses on demographic data, including gender, age, household income range, level of education, and employment status, as well as their current public transport behavior. Section 2 collects information about respondents' experiences with e-scooters, covering aspects such as their e-scooter travel behavior, positive and negative feedback. Section 3 is a stated preference survey aimed at identifying respondents' preferences for First Mile Last Mile (FMLM) travel modes in hypothetical scenarios.

By dividing the survey into these sections, we aim to collect extensive data on the factors influencing FMLM travel preferences among residents of Klang Valley. The stated preference survey was set up using Ngene to generate various combinations of attribute levels for travel time and travel cost for each FMLM travel mode. From these combinations, six situations were selected, and each respondent was asked to answer three randomly assigned questions.

Travel costs for each mode were based on predetermined travel times and current pricing. The e-hailing cost was calculated considering the base fare, travel distance, and travel time (Wong, 2023), while e-scooter pricing was determined based on the unlocking fee and travel duration (Lee, 2023). Rapid Bus pricing was taken from the RapidKL website (Rapid KL - Bus, n.d.). This detailed and structured approach ensures a thorough understanding of the factors influencing travel mode preferences among urban commuters in the Klang Valley.

Table 1 Attribute level for each FMLM travel mode

Experimental Attribute	FMLM Travel Modes	Attribute Levels
Travel Cost	E-Hailing	RM6; RM 12; RM18
	E-Scooter	RM5.50; RM 7.30; RM10.30
	Walking	0
	Rapid Bus	RM1.00; RM1.90; RM2.50
Travel Time	E-Hailing	7 mins; 10 mins; 20 mins;
	E-scooter	7 mins; 10 mins; 15 mins
	Walking	10 mins; 15 mins; 20 mins
	Rapid Bus	15 mins; 20 mins; 25 mins

3.4 Data collection method

The survey was constructed using Qualtrics, leveraging its built-in distribution methods such as anonymous survey links and QR codes. The survey was disseminated through social media platforms and direct messaging (DM) on channels like Instagram, Facebook Messenger, and WhatsApp. While this approach allowed for broad and rapid distribution, it inherently introduced a self-selection bias, as the sample was drawn from individuals who are more likely to engage with online platforms. This limitation affects the generalizability of the findings, particularly in reaching populations less active on social media or those less inclined to participate in online surveys.

After data collection, the data underwent rigorous cleaning and arrangement processes to optimize the dataset for analysis. Each demographic option was categorized into variables, as shown in Table 2. For instance, gender was categorized into three categories: male, female, and prefer not to say/binary, while age was split into three ranges to capture the diversity of the participants' life stages.

Table 2 Data Arrangement

Variable	Option	Category
Gender	Male	1
	Female	2
	Prefer Not to say/Binary	3
Age	<18	1
	19> x <30	2
	>31	3
Level of Education	Secondary School	1
	Undergraduate	2
	Post	3
	Prefers not to say	4
Employment Status	Student	1
	Part Time	2
	Full time	3
	Unemployed	4
Income	B40 (average income RM 3,401)	1
	M40 (average income RM 7,971)	2

	T20 (average income RM 19,752)	3

From Table 2, the gender of the collected data would be categorized into three categories, male, female and prefer not to say or binary. For the age of the participants, it is also split into three parts, younger than 18 for the students, older than 31 for the working class while the in-betweeners are for the young adults. The employment status is categorized to have a more accurate depiction of the participants, which consists of four categories: student, part-time, full-time and unemployed. As for the income status, the participants are all categorized based on the Malaysian income groups: Top 20% (T20) with an average income of RM 19,752, Middle 40% (M40) with an average income of RM 7,971, and Bottom 40% (B40) with an average income of RM 3,401, based on the Department of Statistics' (DOSM) Household Income and Basic Amenities (HIS/BA) survey of 2022.

The analysis was conducted using SPSS's built-in multinomial logit regression model, with the travel mode serving as the dependent variable. Independent variables included demographic factors such as gender, age, education level, employment status, and income group, while covariates like travel time and cost were also considered. The relationships between variables were thoroughly analyzed and verified using backward and forward compatibility testing, ensuring that the model was appropriately specified and that the results were robust.

4 Results and discussion

4.1 Survey data

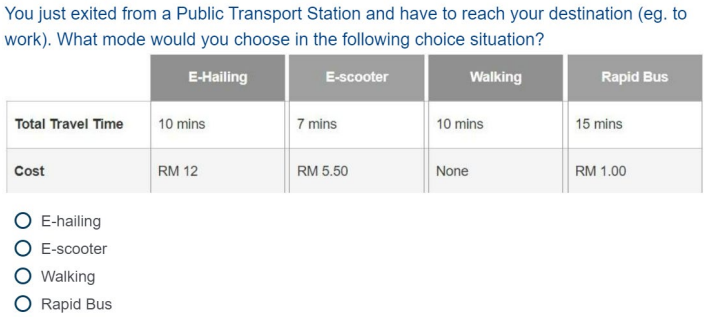
4.1.1 Data collection

Prior to the answering of the survey, the respondents are required to read an "Explanatory Statement" and provide their consent, accepting the terms and conditions of the survey as approved by Monash University. The respondents will receive a set of questions that will include the Stated Preference surveys to collect information regarding their travel behaviour and usage of the e-scooter.

- Section 1 (General): Demographic information and usage public transport
  - Gender, Age, Level of Education, Employment Status, Income Range
  - Current Usage of Public Transport around Kuala Lumpur
- Section 2 (Shared E-scooter):
  - Usage of current shared e-scooter service.
  - The relationship between usage of e-scooter and public transport.
  - Positive and Negative feedbacks regarding shared e-scooter.
- Section 3 (Stated Preference Experiment):
  - A hypothetical situation which shared e-scooter is incorporated as a FMLM transportation mode.
  - To choose a FMLM transport mode between shared e-scooter, e-hailing (a service provided to book public transport services such as taxi, Uber or Grab through electronic applications), walking and public bus.
  - Each transport mode has their respective total travel time and travel cost.

The sample of the stated preference survey is illustrated in Figure 1.

Figure 1 Stated preference survey


You just exited from a Public Transport Station and have to reach your destination (eg. to work). What mode would you choose in the following choice situation?

	E-Hailing	E-scooter	Walking	Rapid Bus
Total Travel Time	10 mins	7 mins	10 mins	15 mins
Cost	RM 12	RM 5.50	None	RM 1.00

- ○ E-hailing
- ○ E-scooter
- ○ Walking
- ○ Rapid Bus

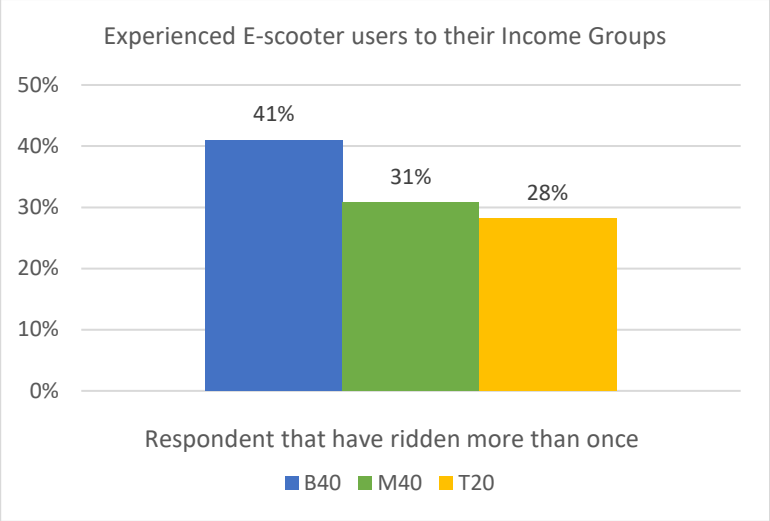
A total of 160 individuals participated in the survey, but after data cleaning and removing of incomplete survey, the final survey respondents' number is narrowed down to 122 individuals. The respondent demographic is shown in, with Figure 2, Figure 3 and Figure 4 showing the revealed preference of the respondent regarding the current e-scooter.

Table 3 Social demographics of respondents

Variables	Categories	Frequency
Gender	Male	53.35%
	Female	46.45%
Age		26.22(7.73)
Level of Education	Secondary School	14.06%
	Undergraduate	46%
	Post-Graduate	39.84%
Employment Status	Student	42.64%
	Part-Time	9.3%
	Full Time	44.19%
	Unemployed	3.88%
Household Income	B40	40.32%
	M40	38.98%
	T20	21.71%

The data gleaned from the survey sample of 122 respondents offers intriguing insights into the demographics of the study. The gender distribution between males and females are roughly 50% each, signaling the survey are not leaned towards any one the gender. As for the age of the respondents, their average age is 26.22, with a standard deviation of 7.73, indicating that most of the respondents are young adults. Based on the percentage split of the education level of the respondents, it is well-educated sample, with the majority holding undergraduate or post-graduate degrees. Furthermore, the household income distribution of the B40 (40.32%), M40 (38.98%), and T20 (21.71%) categories reveal the collected sample's income distribution is similar to of the Malaysian income group. This demographic profile forms a vital foundation for interpreting the survey results and understanding the dynamics of e-scooter adoption in the context of the Klang Valley region.

Figure 2 Percentages split of experienced e-scooter riders



From Figure 2, the experienced e-scooter riders are split into three income groups, which are B40, M40 and T20. The percentage split between are 41 percent, 31 percent and 28 percent respectively. This result is contradictory with the studies done in Singapore which revealed that one of the e-scooter preferences are sided towards high-income demographic.(Cao et al., 2021).

Figure 3 Positive Feedback of E-scooter

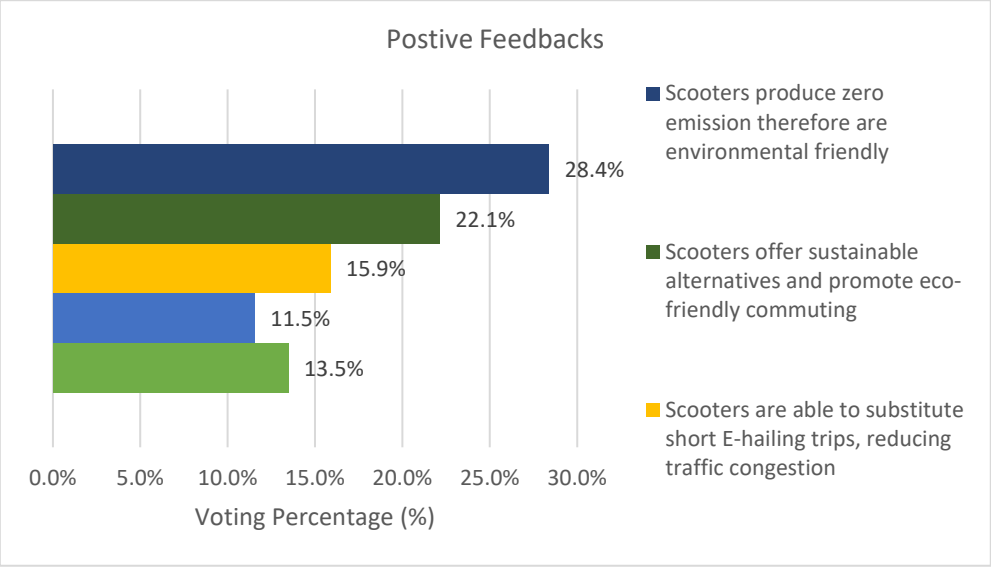
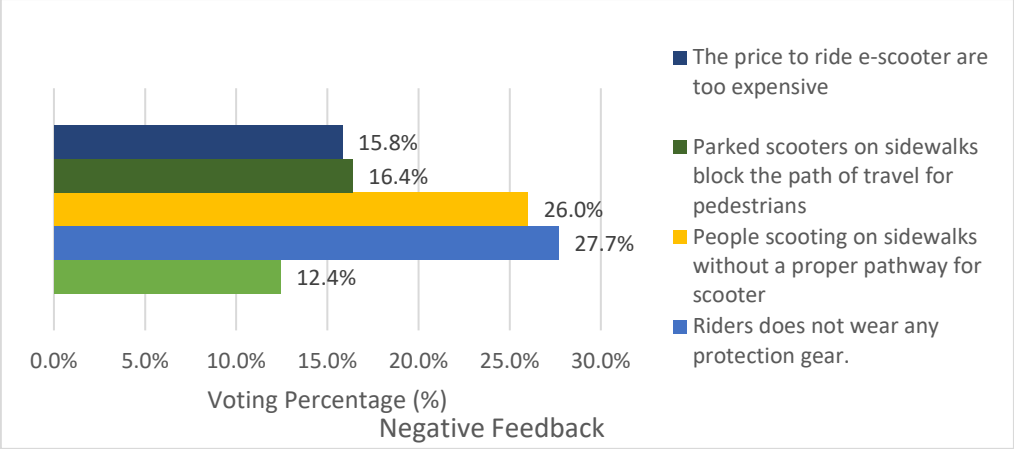


Figure 3 Negative Feedback of E-scooter



At the section 2 of the survey, respondents are provided five negative and positive feedback regarding the current shared e-scooter service for them to vote on in which they resonated most with. According on the negative feedback as shown in Figure 4, the two main problem respondents are most associated with are rider scooting on the sideways without a proper pathway and them riding without any proper protection gear, taking up a total of 53.7% of the votes. Therefore, safety is a key issue for the respondents, which is created by the potential conflict between the pedestrians and e-scooter rider. As for the positive feedback of the e-scooter from Figure 3 about half of the votes, 50.5% to be specific, has been allocated to the feedback categorizing e-scooter as a sustainable and environmentally friendly travel mode. This indicates that the respondents have a strong environmental perception of e-scooters; The ecological aspects of e-scooters are highly emphasized and appealing feature to the respondents. Moreover, with only 13.5% of respondents voted that e-scooters have the potential to become the main FMLM transport, this signals that respondent view e-scooter more as an environmental option than an actual replacement of the FMLM transportation system.

4.1.2 Multinomial Logit Model (MNL) Results

The research used a Multinomial Logit Regression Model (MNL) as the analytical framework to examine the dataset and uncover the complex connections between several factors affecting the travel preferences. The multinomial logit analysis results from SPSS are shown in Table 4 and Table 5, in terms of travel time and travel cost. Through the backward and forward computability test, the analysis revealed statistically significant relationships between variables. For travel time, it is found out that age, income range and gender of the respondents are correlated with the FMLM transport preference of the respondent. But as travel cost is included in the compatibility test with travel time, the results of the MNL model become invalid.

Table 4 MNL results for Travel Time

Parameter Estimates									
Mode Input[a]		B	Std. Error	Wald	df	Sig.	Exp(B)	95% Confidence Interval for Exp(B)	
								Lower Bound	Upper Bound
E-hailing	Intercept	2.429	1.010	5.782	1	.016			
	Age	-.017	.019	.767	1	.381	.983	.947	1.021
	Travel Time	-.193	.076	6.459	1	.011	.825	.711	.957
	Male	-.049	.319	.023	1	.879	.952	.509	1.781
	Female	0[b]	.	.	0	.	.	.	.
	B40	-1.007	.498	4.083	1	.043	.365	.138	.970
	M40	-.198	.408	.236	1	.627	.820	.369	1.824

	T20	0[b]	.	.	0	.	.	.	.
Walking	Intercept	-1.867	1.076	3.012	1	.083			
	Age	-.095	.029	10.913	1	.001	.909	.859	.962
	Travel Time	.423	.063	45.380	1	.000	1.527	1.350	1.728
	Male	1.037	.369	7.889	1	.005	2.820	1.368	5.814
	Female	0[b]	.	.	0	.	.	.	.
	B40	-1.088	.491	4.898	1	.027	.337	.129	.883
	M40	-1.566	.487	10.338	1	.001	.209	.080	.543
	T20	0[b]	.	.	0	.	.	.	.
Rapid Bus	Intercept	-8.444	1.553	29.579	1	.000			
	Age	-.056	.038	2.197	1	.138	.945	.878	1.018
	Travel Time	.739	.078	89.097	1	.000	2.093	1.796	2.440
	Male	.788	.490	2.588	1	.108	2.200	.842	5.747
	Female	0[b]	.	.	0	.	.	.	.
	B40	-1.002	.649	2.382	1	.123	.367	.103	1.310
	M40	-1.506	.668	5.078	1	.024	.222	.060	.822
	T20	0[b]	.	.	0	.	.	.	.

a. The reference category is: E-scooter.

b. This parameter is set to zero because it is redundant.

The provided data stems from a logistic regression analysis, offering detailed insights into the factors that influence the choice of travel mode compared to the reference category, "E-Scooter." Notably, for E-Hailing, an extended travel time has a notable impact, with each additional unit of travel time leading to a significant 17.2% decrease in the likelihood of choosing E-Hailing. Age and gender, on the other hand, do not significantly sway the choice of E-Hailing. However, the "B40" income group is associated with a marginally significant 62.7% reduction in the odds of opting for E-Hailing. Moving to the Walking mode, the analysis reveals that each year of age equates to a significant 9% decrease in the likelihood of choosing Walking. Each unit increase in travel time increased the percentage of choosing walking over e-scooter by 52.7%. In contrast to being female, being male increases the odds of selecting Walking by approximately 215.2%. As for the income group, both “B40” and “M40” are less likely to choose Walking over E-scooter. Lastly, for Rapid Bus, travel time stands out as a prominent driver, with each additional unit increasing the odds of choosing Rapid Bus by approximately 114.8%. Age and gender, however, have no significant impact on the choice of Rapid Bus. The B40 income group also shows a trend towards lower likelihood but is not significant. The M40 income group is significantly less likely to choose Rapid Bus, indicating a notable income effect on this travel mode preference. These findings provide valuable insights into the specific effects of age, travel time, gender, and age groups on the selection of travel modes, expressed as percentage changes in the likelihood of choosing a particular mode over E-Scooter.

Table 5 MNL Result for Travel Cost

Parameter Estimates									
								95% Confidence Interval for Exp(B)	
Mode Input[a]		B	Std. Error	Wald	df	Sig.	Exp(B)	Lower Bound	Upper Bound
	Intercept	-2.528	.558	20.523	1	.000			

E-hailing	Travel Cost	.292	.067	18.960	1	.000	1.340	1.174	1.528
Walking	Intercept	78.916	41105.818	.000	1	.998			
	Travel Cost	-62.406	.000	.	1	.	7.897E-28	7.897E-28	7.897E-28
Rapid Bus	Intercept	50.649	45439.392	.000	1	.999			
	Travel Cost	-13.395	9560.114	.000	1	.999	1.523E-6	.000	.[b]

a. The reference category is: : E-scooter.

b. Floating point overflow occurred while computing this statistic. Its value is therefore set to system missing.

In this analysis, travel cost significantly influences the choice of E-Hailing, as an increase in Travel Cost is associated with a 34.1% higher likelihood of opting for E-Hailing, reflecting the perception of enhanced convenience or reliability with increased cost. However, for the choice of Walking and Rapid Bus, several concerns arise. The remarkably high intercept values, along with extremely high and low standard errors, raise doubts about the model's reliability. Additionally, the extremely low coefficient values for Travel Cost and the close-to-one p-values (0.999) suggest that Travel Cost does not have a significant impact on the choice of Walking or Rapid Bus in this dataset.

4.1.3 Limitations and future work

The method employed for distributing surveys through social media and direct messaging has inherent limitations that impact the representativeness of the sample. It is important to note that this sampling strategy leaned more towards convenience sampling rather than the preferred approach of ideal random sampling. Consequently, the survey data collected may exhibit a notable bias towards a specific demographic group. This potential bias becomes a pivotal concern because the proportions of these demographics could exert a considerable influence on the overall survey results.

For instance, an examination of the respondent demographics reveals that the average age of respondents stands at 26 years, with a standard deviation of 7 years. This indicates a skew towards younger individuals, which in turn, raises concerns about the generalizability of the findings to a broader population, particularly older age groups. As a result, the responses obtained concerning e-scooters may be contingent upon the specific demographic group primarily represented in the survey. In effect, this sampling limitation underscores the need for caution when extrapolating the findings to a wider and more diverse population, as it may not accurately capture the perspectives and behaviors of individuals who were not adequately represented in the survey.

To address these limitations, future research could incorporate more diverse distribution methods, such as random sampling from a comprehensive population database or using mixed-mode surveys that include both online and offline respondents. Additionally, conducting follow-up studies in different geographic areas or with different demographic groups would help validate the findings and enhance their generalizability.

Moreover, the stated preference survey was designed to balance comprehensiveness with manageability by focusing on key transportation modes. However, this meant that some modes like taxis, bike-sharing, and private bikes were excluded. Future iterations of the survey should consider expanding the choice set to include these additional modes, providing a more holistic view of respondents' transportation preferences. This flexibility will

allow the research to adapt to the evolving landscape of transportation options, ensuring a more thorough understanding of user preferences.

Another limitation of this research is its focus on average conditions, such as traveling on paved surfaces in moderate temperatures. This focus may introduce bias towards certain transportation modes like cars and public transport, which are more versatile under varied conditions. Future research should consider a wider range of environmental and situational factors, such as extreme weather conditions, varying terrain, and specific travel purposes, which could significantly influence transportation mode choices. For example, while the survey did not explicitly differentiate between travel purposes, recognizing that different purposes (e.g., commuting, leisure, errands) can influence mode preference is crucial. Future surveys should capture these nuances to provide a more detailed understanding of how and why individuals choose specific transportation modes.

In conclusion, while this study provides valuable insights into the benefits and barriers of e-scooter usage, addressing these limitations will enhance the robustness and generalizability of future research. By refining the sampling methods, expanding the choice set, and considering a broader range of conditions and travel purposes, future studies can offer more comprehensive and actionable insights into the dynamics of e-scooter adoption and other transportation modes.

5 Conclusion

In conclusion, this study has provided valuable insights into the dynamics of e-scooter adoption and the factors influencing travel mode choices among urban commuters in the Klang Valley. This study provides valuable insights into the role of e-scooters as a First Mile Last Mile (FMLM) transport option and highlights how income levels influence their adoption. These insights are critical for developing targeted policies that enhance the accessibility and inclusivity of e-scooter services in urban areas.

The research sample of 122 respondents has revealed a diverse demographic profile, with a skew towards younger individuals, reflecting the online nature of the survey and its appeal to this population. The predominance of males and respondents with higher education levels further characterizes the sample. One of the key findings of this research is the popularity of e-scooters among the lower-income B40 group, suggesting that e-scooters are perceived as a cost-effective alternative for short trips. Additionally, the appeal of e-scooters extends to higher-income households, highlighting their convenience and flexibility. Safety emerged as a significant concern among respondents, particularly regarding riders using sidewalks without proper pathways and not wearing protective gear. This underscores the importance of addressing safety concerns to encourage e-scooter adoption. On a positive note, the environmental friendliness of e-scooters was a notable advantage, with half of the respondents associating e-scooters with sustainability and eco-friendliness.

The research employed a Multinomial Logit Regression Model (MNL) to analyse the dataset and investigate the intricate relationships influencing travel mode preferences. Statistically significant relationships emerged in the context of travel time, revealing that age, income range, and gender of respondents are correlated with First Mile Last Mile (FMLM) transport preferences. Notably, extended travel time significantly reduced the likelihood of choosing E-Hailing, whereas being male increased the odds of selecting Walking. The analysis also unveiled the importance of travel time as a driver for the choice of Rapid Bus. However, Travel Cost significantly impacted the preference for E-Hailing, reflecting the perception of increased convenience with higher costs. For Walking and Rapid Bus, concerns regarding model reliability and insignificant effects of Travel Cost were observed, prompting further investigation into these areas. These findings offer valuable insights into the nuanced interplay of factors affecting travel mode selection, providing a foundation for future research and policy development in urban transportation planning.

However, it is important to acknowledge certain limitations of this study. The survey distribution method through social media and direct messaging resulted in a sample that may not be fully representative of the broader population. The survey skewed towards a younger demographic, raising concerns about generalizability to older age groups. Additionally, the choice set in the stated preference survey was constructed to be manageable, and some transportation modes were excluded. Future research can consider expanding the choice set to capture a more comprehensive range of preferences.

In summary, this study has highlighted critical factors influencing e-scooter adoption and travel mode preferences in the Klang Valley. It underscores the need to address safety concerns, particularly regarding infrastructure and protective gear, while also emphasizing the environmental benefits of e-scooters. Although the study's sample and choice set were somewhat limited, the findings offer a robust foundation for policymakers and urban planners to enhance sustainable transportation solutions. Future research should aim to include a more diverse demographic and a broader range of transportation modes to build on these findings and further inform urban transportation policies.

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