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Willingness to Use Shared Micro-Mobility Services Among **Unhappy Campus Bus Riders: An Ordinal Regression Analysis**

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Abstract

Increasing users is a challenge for shared micro-mobility services at the university, but it is necessary for achieving their full potential. Students with negative experiences with the campus bus service (termed unhappy campus bus riders) may be attracted to micro-mobility due to its flexibility, convenience, and support for sustainable transport goals. Thus, this study aims to evaluate unhappy bus riders' willingness to use micro-mobility in different scenarios. An online questionnaire was prepared for data collection, with distinct sections designed to gather both revealed and stated preferences. Revealed preference was used to identify students with negative experiences on campus buses. Then, nine scenarios based on micro-mobility adoption barriers were presented in a stated preference section to gauge unhappy bus riders' willingness to use micro-mobility under hypothetical situations. By applying ordinal logit regression analysis on the survey data collected from 308 respondents living on the main campus of the National University of Malaysia, it is found that four out of seven types of bus experiences significantly affect unhappy bus riders' willingness to use micro-mobility in three scenarios. The results from regression analyses proposed four separate ordinal logit models, each with a single type of negative experience as a predictor variable to calculate the likelihood of micro-mobility use in the future. We believe that the findings of our study can help the university's mobility department identify a new micro-mobility user segment. Consequently, they can devise specific strategies to promote micromobility options for students travelling short distances on campus.

Keywords: Campus Bus Service, Micro-Mobility, Ordinal Logit Model, Sustainable Transportation, Transport Switching, Travel Experience.

Introduction

Most university students depend greatly on bus services to get to and from campus. One of the primary reasons is campus buses' affordability compared to owning and maintaining a car or motorcycle, which can be a significant financial burden for many students (1). Additionally, most public universities provide discounted or complimentary bus passes, encouraging students to utilise the bus even more. Regarding traffic safety, buses offer a far lower risk of being involved in a traffic accident. Consequently, students feel safer riding a bus operated by a trained driver (2). This sense of safety and convenience that comes with bus travel is vital, especially during peak hours. Accessibility, environmental concern, and lack of alternatives are other factors that influence individuals' transportation choices. For highereducation students living on campus, access to an efficient bus service is essential to accommodate their busy daily schedules and commitments.

Inefficient bus services can cause students to arrive late for lectures and co-curricular activities. Arriving late to class affects students' moods. These mood swings can disrupt learning performance, particularly at the start of the class (3). If this unpleasant situation occurs repeatedly, it may hinder students from reaching their full potential in academic and disrupt their motivation to maintain good time management (4). The inefficiency of the campus bus creates consequences that are not only seen in delays but also result in longer waiting times, inconsistent schedules, and uncertain arrival times. In addition to being inefficient, negative travel experience can also arise from uncomfortable rides caused by overcrowding or inadequate vehicle maintenance, as well as insufficient infrastructure, such as poorly designed bus stops and the absence of realtime information systems (5, 6). Experiencing repeated negative encounters with the campus bus

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over a semester can lead to a decline in students' satisfaction with the service. Dissatisfaction with campus bus services could develop students' desire to change how they prefer to commute each day. They may research different modes of transport, compare costs and benefits, or even experiment with new options to see if they provide a better fit (7). As micro-mobility services gain popularity in universities, students will likely evaluate this new mobility option.

Micro-mobility options such as powered bicycles, powered scooters, powered self-balancing/non self-balancing boards, or powered skates offer greater control, flexibility, and comfort for daily commutes and recreational purposes (8). As mobility trends in the university setting progress towards micro-mobility (9), it becomes apparent that micro-mobility solutions offer promising advantages. Indeed, micro-mobility options are environmentally friendly, producing low greenhouse gas emissions, and they are vital for fostering a clean, healthy, and high-quality environment (10). Students may transition to micro-mobility options, especially if it addresses their concerns and offers a more satisfying experience. Therefore, it is essential to promote micro-mobility adoption within university settings while also addressing the demands for environmental sustainability. This transition can reduce students' dependence on campus bus services, especially during peak times.

Although micro-mobility presents an environmentally friendly option compared to conventional transportation modes, switching barriers hinder the widespread adoption of micromobility services. Safety concerns, cost, and weather prevent micro-mobility from becoming a more attractive alternative for short-distance trips. First-time users frequently experience a sense of insecurity when using micro-mobility due to infrastructure-related factors such as dedicated lanes, which exposes them to potential risks of traffic incidents (11). Additionally, sharing sidewalks with pedestrians can create conflicts and potential injuries for both parties (12). Another safety concern is the lack of guidelines on the top speed of electric scooters (13). This lack of clarity arises from their ability to travel up to 30 km/hour. For many individuals, especially students, the initial costs of purchasing a personal micro-mobility vehicle can be a significant barrier, particularly considering the relatively high cost of devices with sufficient range and endurance (14). While shared mobility services may appear more affordable at first glance, the per-minute or pertrip fees can quickly add up, making them less practical for regular use, especially for longer commutes. Additionally, micro-mobility users are more likely to encounter weather-related challenges (15), as illustrated by their preference for using shared micro-mobility services primarily during mild morning and evening hours on weekdays (16).

A potential new segment of micro-mobility users may emerge from campus bus riders who had negative experiences, referred to as "unhappy bus riders". However, it remains unclear whether these individuals will adopt micro-mobility options, even with the removal of barriers to adoption. This study investigates the willingness of unhappy bus riders to transition to micro-mobility under various scenarios with different switching barriers. We address two research questions: (a) which negative experiences with campus buses significantly impact university students' willingness to use micro-mobility options? (b) In which scenarios are the differences in willingness to adopt micro-mobility statistically significant? We employed a two-pronged approach. First, we conducted a revealed preference survey to identify unhappy campus bus riders and used Chi-square independence tests to identify which negative bus experiences could predict the likelihood of choosing micro-mobility. Second, we developed ordinal regression models to determine whether these unhappy riders would be more or less likely to use micro-mobility in the future if barriers to adoption were addressed.

Findings of the study offer valuable insights for campus transportation planning by identifying a potential new group of micro-mobility users: unhappy bus riders. Encouraging this group to adopt micro-mobility could alleviate bus overcrowding, particularly during peak hours, while promoting a healthier lifestyle. Additionally, this initiative aligns with university efforts to enhance sustainability.

Methodology

This study utilised an ordinal logit regression analysis to determine whether university students with negative experiences on the campus bus service are more or less likely to use micromobility in the future if adoption barriers to new users are eliminated. Based on the literature

review presented above, the research model in this study is shown in Figure 1.



Figure 1: Research Model

Data collection was conducted at the main campus of UKM (National University of Malaysia) located in Educational City, Bandar Baru Bangi. The UKM main campus represents a dynamic and diverse academic community with a substantial student population actively engaging with various campus transportation options. Conducting this study at the main campus allows us to explore various situations in which micro-mobility might be adopted in a metropolis setting (17). The study's findings inform the transportation planner at the university about a new micro-mobility user segment, potentially paving the way for integrating micro-mobility into a comprehensive and ecofriendly campus mobility plan.

Data for this study was collected through a selfadministered online questionnaire comprising three sections. In the first section (Section A), respondents indicated their experience with the UKM bus service by selecting 0 = No or 1 = Yes foreach statement relating to bus service. Seven statements, four and three respectively, addressed two categories of bus service quality that shape traveller's experience (18, 19): on-board comfort and trip time reliability. Data from this section were subsequently used to regress the commuting experience by campus bus against the likelihood of using micro-mobility vehicles in the future. The following section (Section B) employed a stated preference (SP) approach to investigate respondents' potential use of micro-mobility in various scenarios on UKM's main campus. Nine hypothetical situations related to barriers in micro-mobility adoption were presented, and respondents indicated their likelihood of use on a three-point Likert scale (1=Unlikely, 2=Likely, 3=Very likely). Table 1 describes the items/statements regarding bus riding experience and SP questions used for the questionnaire in this study (19, 20). In the final section (Section C), respondents provided background information, including their travel characteristics within the campus area.

Scale	Dimension	Statement on Survey (Item)	Code
Experience of	Trip time	i. I arrived late to class due to bus delays.	A1
travelling by	reliability	ii. I missed the bus because the schedule	was A2
campus bus		changed without notice.	
		iii. I had to wait for the bus longer than I expec	ted. A3
		iv. The bus journey took longer than I expected	l. A4
	Comfort	v. The bus was overcrowded, making the jou uncomfortable.	ırney A5
		vi. I felt bothered by unpleasant smells travelling on the bus.	while A6

Table 1: Items of Each Scale Included in the Survey Instrument

	vii.	The noise inside the bus made my journey stressful.	A7
Willingness to Safety use micro-	i.	Micro-mobility vehicles have dedicated lanes	B1
mobility	ii.	Wearing helmets and safety vests is optional.	B2
	iii.	Micro-mobility vehicles are equipped with automatic speed limiters.	В3
	iv.	Micro-mobility technology is safety-certified by a regulatory agency.	B4
Conveni	ence v.	Access to available micro-mobility vehicles is granted by scanning a student card.	B5
	vi.	Secure and easily accessible storage is provided for micro-mobility vehicles.	B6
	vii.	Micro-mobility access points are located within 50 meters of a residential area.	B7
	viii.	Usage fees start as low as RM1 (~\$0.25 USD) per	B8
		trip.	B9
	ix.	Weather conditions favour micro-mobility use (e.g., no rain, moderate temperatures).	

A pilot study assessed the internal reliability of items used in Sections A and B of the questionnaire. This step identified and addressed issues related to clarity, comprehensibility, and suitability of the measurement items in those sections, allowing for necessary improvements before the actual survey. After analysing responses from 30 UKM students in the pilot study, Cronbach's Alpha for items in Sections A and B was found to be 0.69 and 0.72, respectively, indicating good reliability. This study conducted an ordinal regression analysis to quantify the relationship between negative experiences with campus buses and university students' willingness to use micro-mobility in different scenarios. The resulting models calculated the odds of unhappy bus riders being likely or very likely to use micro-mobility for nonrecreational purposes within the campus area. The general formula for an ordinal logit (natural logodds) model with a single categorical predictor variable X having k levels can be expressed as follows:

$$\ln\left(\frac{P(Y \le j)}{P(Y > j)}\right) = \alpha_j + \sum_{i=1}^{k-1} \beta_i D_i \quad [1]$$

where Y is the ordinal dependent variable having J ordered categories. $P(Y \le j)$ is the cumulative probability at or below the j-th category. P(Y > j) is the complementary probability. We

for X as denote dummy variable the D_1, D_2, \dots, D_k . These dummy variables are defined as follows: $D_i = 1$ if X is in level *i*, $D_i = 0$ otherwise. α_j is the intercept for outcome category j. The ordinal logit model will have J-1intercepts. β_i are the coefficients for dummy variables representing levels of X. *i* goes from 1 to k minus 1. The term 'minus 1' denotes the reference category. The reference category (or group) is typically defined as the most frequent or dominant level within a predictor variable. In the ordinal logit model, the event of interest calculates the odds of being in a higher category of an outcome variable. Suppose an ordinal outcome variable has three categories: unlikely to use micro-mobility, likely, and very likely. The ordinal logit model would estimate the log-odds to be in a higher category of micro-mobility usage intention (i.e., more likely to choose likely or very likely).

models to examine how prior experiences with campus bus services $\begin{pmatrix} X \end{pmatrix}$ may influence students' intention to use a micro-mobility $\begin{pmatrix} Y \end{pmatrix}$ across different scenarios. Nine distinct scenarios were presented to respondents, and for each scenario, respondents indicated their likelihood of using micro-mobility on an ordinal scale (*j*=1 is unlikely,

This study constructed separate ordinal logit

j=2 is likely, *j*=3 is very unlikely). Seven different experiences with campus bus (e.g., on-board comfort, trip time reliability) were analysed, each serving as a predictor variable in a separate ordinal logit model. Each experience with bus service was coded as a binary variable (0 if experienced, 1 otherwise), with the not experienced category serving as the reference. The exponentiated coefficients from the ordinal logit models represent the cumulative odds ratios of being more likely to use micro-mobility in the future relative to those who did not have the corresponding experience. Parameters of ordinal logit models were estimated using the PLUM (PoLytomus Universal Model) procedure in SPSS ver.27.

Results

A total of 308 students living on the main campus of UKM participated in this study. Most respondents (71.8%) identified as female, while 28.2% identified as male. Most respondents fell within the age range of 21 to 23 years (66%) followed by the 18-20 age group (27.2%). Almost all the participants (97. 4%) were in degree programs, with a small number pursuing foundation (2.6%) or master's degrees (less than 0.3%). Most respondents (72.7%) used the UKM bus service more than twice a week, while 27.3% did not use the service as frequently. Additionally, most respondents (87%) did not own a micromobility vehicle on campus, with only 13% owning one. Table 2 presents (basic) statistics on survey respondents' demographics, bus service usage, and micro-mobility ownership.

N=308		Count	Percentage
Gender	Male	87	28.2%
	Female	221	71.8%
Age group	18 - 20	84	27.3%
	21 - 23	203	65.9%
	24 and above	21	6.8%
Program of study	Foundation study	4	1.3%
	Undergraduate	300	97.4%
	Postgraduate	4	1.3%
Do you use the UKM bus service more than twice	Yes	224	72.7%
a week?	No	84	27.3%
Do you own a micro-mobility on campus?	Yes	40	13.0%
	No	268	87.0%

Table 2: Summary of Respondent Information

One of the objectives of this study was to determine the percentage of UKM students who have encountered negative experiences while using the campus bus service. The survey results in Figure 2 revealed that most respondents had experienced issues with trip time reliability (B1-B4) and on-board comfort (B5-B7). When it comes to the reliability of travel time, the most common issues are waiting times longer than expected (84.7%), changes to the bus schedule without notice (71.1%) and buses arriving late (69.5%).

Regarding the on-board comfort, the most frequently reported issues during the trip are overcrowding (83.4%) and excessive noise (58.8%).

Interestingly, almost half of respondents (49.7%) have not experienced an issue with unpleasant smells on campus buses that can lead to discomfort and even anxiety for some individuals.



Figure 2: Distribution of Responses for Each Question Regarding Bus Travel Experiences

As mentioned in the methodology section, students' willingness to use micro-mobility was analysed through nine potential scenarios. The distribution of responses for each scenario is shown in Figure 3. The results suggested that the willingness to use micro-mobility vehicles in the future was generally well-received, with varying degrees of willingness associated with the specific conditions. The assurance of safety in micromobility technology and convenient scanning access via student cards received very likely responses from 82.8% and 81.5% of respondents, respectively. Secure and conveniently reachable storage was also identified as an important feature, as 79.5% of participants indicated a solid inclination to adopt micro-mobility services under Dedicated lanes such circumstances. were identified as one of the top five important features, with 68.8% of respondents responding that they would likely use micro-mobility if such lanes were available. Surprisingly, making helmets and vests optional did not significantly discourage respondents, with 39.3% indicating they would be likely and 31.8% very likely to use micro-mobility under these conditions. Finally, most respondents also rated weather, access point locations within 50 meters, and automatic speed limiters as important features in micro-mobility adoption.



Figure 3: Respondent Preferences for Micro-mobility Usage under Various Scenarios The primary goal of this study is to explore the potential effects of past negative experiences with campus bus services on students' willingness to use micro-mobility options within the campus. Separate ordinal logit models as explained in Eqn. [1] were constructed to regress the experience of

travelling by campus bus against the likelihood of using micro-mobility vehicles. In this study, the regression analysis focused only on types of experiences that exhibited a statistically significant association with the response variable, as determined by preliminary Chi-square tests of independence. Potential predictor variables for the ordinal logit models are highlighted in yellow in Table 3. For example, the result of the Chi-square test (χ^2 = 9.026, df = 2, *p*-value = .011) revealed that there is a statistically significant association between experiencing longer than expected travel times by bus (A4) and a student's willingness to

use micro-mobility when the access to micromobility is granted by a student card (B5). The value of Chi-square ($\chi^2 = 11.488$, df = 2, *p*-value = .003) also suggested that there was a statistically significant association between experiencing disruptive noise levels on buses (A7) and B5.

		B1	B2	B3	B4	B5	B6	B7	B8	B9
A1	Chi- square	0.252	3.931	0.993	1.903	1.381	3.319	1.987	8.222	2.078
	<i>p</i> -value	0.882	0.140	0.609	.386	0.501	.190	0.370	.016*	0.354
A2	Chi- square	6.871	1.741	4.453	2.481	1.321	1.456	0.276	4.344	0.697
	<i>p</i> -value.	.032*	0.419	0.108	.289	0.517	.483	0.871	0.114	0.706
A3	Chi- square	2.596	5.798	1.822	1.111	1.826	2.807	0.345	0.160	2.067
	<i>p</i> -value	0.273	0.055	0.402	.574	0.401	.246	0.841	0.923	0.356
A4	Chi- square	1.382	1.382	0.227	0.315	9.026	0.152	3.239	3.269	2.521
	<i>p</i> -value	0.501	0.501	0.893	.854	.011*	.927	0.198	0.195	0.284
A5	Chi- square	0.224	6.838	1.102	4.827	4.642	0.820	1.995	3.479	0.633
	<i>p</i> -value	0.894	.033*	0.576	.090	0.098	.664	0.369	0.176	0.729
A6	Chi- square	2.712	3.418	3.977	0.011	6.509	0.689	2.028	1.045	0.767
	<i>p</i> -value	0.258	0.181	0.137	.994	.039*	.709	0.363	0.593	0.681
A7	Chi- square	3.430	3.920	3.140	2.872	11.488	0.204	1.301	2.374	0.522
	<i>p</i> -value	0.180	0.141	0.208	.238	.003*	.903	0.522	0.305	0.770

Table 3: Results of Chi-Square Independence Tests

Note: * The Chi-square statistic is significant at the .05 level

Following the Chi-square independence tests, we constructed six single-factor logit models: M1-M6 (see Table 4). B5 was the most frequently used dependent variable among these models, appearing in three out of six ordinal logit models. An ordinal regression analysis relies on the proportional odds assumption, which states that the relationship between each pair of response categories is consistent across all levels of the predictor variables. This assumption implies that the parameters of an ordinal logit model can describe the relationships between all levels of the ordinal response. Parallel line tests, often implemented using the log-likelihood ratio test, were performed in this study to assess the validity of this assumption. The assumption of parallel lines was not violated in models M2-M5 as evidenced by the non-significant Chi-square values for the Test of Parallel Lines (*p*-value > 0.05). This result indicates that the relationship between a predictor variable and the response variable is consistent across different response variable categories for each of the four models. For models M1 and M6, the parallel line test was statistically significant (*p*-value < 0.05), which means the proportional odds assumption for the models was violated. Given the violation of the assumption of proportional odds, both M1 and M6 were excluded from the subsequent analyses that rely on this assumption.

In the context of model fitting information, a statistically significant Chi-square test (*p*-value <

0.05) indicates that the inclusion of the predictor variable has led to a significant improvement in the model's fit compared to the intercept-only model (a model with no predictors). From Table 4, the models M2-M5 exhibited statistically significant improvements in fit compared to an intercept-only model. These statistics suggest that variables A1, A4, A5 and A6 are significantly associated with their respective response variables in an ordinal regression model. Despite the relatively low pseudo R-square values (Cox and Snell, Nagelkerke, McFadden), i.e., less than 0.10, which suggest that variables A1, A4, A5 and A6 may not explain a large proportion of the variance in the

outcomes when considered alone, the significant Chi-square values in the model fitting information indicate these variables, when formulated in their respective models, are still statistically significant in explaining differences in the outcome variable. Overall, models M2-M5 sufficiently predict the outcomes for the respective dependent variables as evidenced by non-significant Chi-square values for both Pearson and Deviance tests (*p*-value > 0.05). This result indicates no statistically significant difference between the observed and expected values. The larger observed significance levels for M3 and M5 indicate a superior fit compared to models M2 and M4.

	Dependent variable	B1	B8	B2	B5	B5	B5
	Explanatory variable	A2	A1	A5	A4	A6	A7
Test	Model	M1	M2	M3	M4	M5	M6
Test of Parallel Lines	Null Hypothesis (-2 Log Likelihood) General (-2 Log	24.282	21.867	19.795	18.408	16.196	21.941
	Likelihood)	14.798	19.576	19.538	16.225	16.193	15.965
	Chi-Square	9.484	2.291	0.257	2.183	0.004	5.976
Model Fitting	Sig. Intercept Only (-2 Log	0.002ª	0.13	0.612	0.14	0.952	0.015 ^a
Information	Likelihood)	26.076	27.293	26.131	24.946	22.782	27.397
	Final (-2 Log Likelihood)	24.282	21.867	19.795	18.408	16.196	21.941
	Chi-Square	1.794	5.426	6.336	6.538	6.586	5.455
	Sig.	0.180 ^b	0.02	0.012	0.011	0.01	0.020
Pseudo							
R-Square	Cox and Snell	0.006	0.017	0.020	0.021	0.021	0.018
	Nagelkerke	0.007	0.021	0.023	0.031	0.031	0.026
	McFadden	0.004	0.009	0.009	0.019	0.019	0.016
Goodness-of-							
Fit	Pearson (Chi-Square)	6.045	2.27	0.257	2.187	0.004	5.932
	Pearson (Sig.)	0.014 ^c	0.132	0.612	0.139	0.952	0.015 ^c
	Deviance (Chi-Square)	9.484	2.291	0.257	2.183	0.004	5.976
	Deviance (Sig.)	0.002 ^c	0.13	0.612	0.14	0.952	0.015 ^c

Table 4: Testing Results

Note: a Proportional odds assumption violated, b No significant improvement, c Significant differences in response

Table 5. Farameter Estimates for Four Selected Logit Models									
Model			Estimate	Std. Error	Wald	df.	Sig.		
M2 Threshold	Unlikely = 1	-1.587	.299	48.201	1	<.001			
(A1, B8)	Threshold	Likely = 2	0.081	.129	0.166	1	.684		

Table 5: Parameter Estimates for Four Selected Logit Models

Location	Experienced = 0	.565	.239	5.582	1	.018
	No experience = 1	0 ^a				
Threshold	Unlikely = 1	-1.526	.280	29.626	1	<.001
	Likely = 2	.164	.266	.381	1	.537
Location	Experienced = 0	727	.289	6.333	1	.012
Location	No experience = 1	0 ^a				
Threshold	Unlikely = 1	-3.097	.368	70.697	1	<.001
Inresnoid	Likely = 2	-1.053	.213	24.387	1	<.001
T	Experienced = 0	.757	.296	6.520	1	.011
Location	No experience = 1	0 ^a				
Threshold	Unlikely = 1	-3.186	.355	80.358	1	<.001
	Likely = 2	-1.143	.189	36.786	1	<.001
Location	Experienced = 0	.766	.304	6.329	1	.012
	No experience = 1	0 ^a				
	Location Threshold Location Threshold Location Threshold Location	LocationExperienced = 0 No experience = 1 Unlikely = 1 Likely = 2ThresholdUnlikely = 1 Experienced = 0 No experience = 1ThresholdUnlikely = 1 Likely = 2LocationExperienced = 0 No experience = 1ThresholdUnlikely = 1 Likely = 2LocationUnlikely = 1 Likely = 1 Likely = 2ThresholdExperienced = 0 No experience = 1ThresholdUnlikely = 1 Likely = 2LocationExperienced = 0 No experience = 1	Location Experienced = 0 .565 No experience = 1 0^a Threshold Unlikely = 1 -1.526 Likely = 2 .164 Location Experienced = 0 727 No experience = 1 0^a Threshold Unlikely = 1 -3.097 Likely = 2 -1.053 Location Experienced = 0 .757 No experience = 1 0^a Threshold Unlikely = 1 -3.186 Likely = 2 -1.143 Location Experienced = 0 .766 No experience = 1 0^a	Location Experienced = 0 .565 .239 No experience = 1 0^a .280 Threshold Unlikely = 1 -1.526 .280 Likely = 2 .164 .266 Location Experienced = 0 .727 .289 No experience = 1 0^a . Threshold Unlikely = 1 -3.097 .368 Location Unlikely = 2 -1.053 .213 Location Experienced = 0 .757 .296 No experience = 1 0^a . . Location Unlikely = 1 -3.186 .355 No experience = 0 .766 .304 . Location Experienced = 0 .766 .304	LocationExperienced = 0.565.2395.582No experience = 1 0^a 0^a 29.626ThresholdUnlikely = 1-1.526.28029.626Likely = 2.164.266.381LocationExperienced = 0727.2896.333No experience = 1 0^a ThresholdUnlikely = 1-3.097.36870.697Likely = 2-1.053.21324.387LocationExperienced = 0.757.2966.520No experience = 1 0^a ThresholdUnlikely = 1-3.186.35580.358Likely = 2-1.143.18936.786LocationExperienced = 0.766.3046.329No experience = 1 0^a	LocationExperienced = 0.565.2395.5821No experience = 1 0^a 0^a 111ThresholdUnlikely = 1-1.526.28029.6261Likely = 2.164.266.3811LocationExperienced = 0727.2896.3331No experience = 1 0^a 0^a 0^a 0^a 0^a ThresholdUnlikely = 1-3.097.36870.6971Likely = 2-1.053.21324.3871LocationExperienced = 0.757.2966.5201No experience = 1 0^a 0^a 0^a 0^a ThresholdUnlikely = 1-3.186.35580.3581LocationLikely = 2-1.143.18936.7861LocationExperienced = 0.766.3046.3291No experience = 1 0^a 0^a 0^a 0^a

Note:Link function: Logit

^a This parameter is set to zero because it is redundant

Using the estimated coefficients from Table 5, we will now predict the likelihood of micro-mobility usage in three scenarios: B2, B5 and B8, explicitly focusing on students who have had negative experiences with campus buses. In Table 5, the estimate labelled *Location* represents the coefficient for the predictor variable in each ordinal model (e.g., 0.565 is the coefficient for A1 predicting B8). On the other hand, the estimate labelled *Threshold* defines the cut-points between the different levels of students' willingness to use micro-mobility. For example, the threshold estimate of -1.587 in model M2 is the cut-point between the unlikely to use and the combined likely or very likely categories.

The Wald statistic (5.582) for A1 with a *p*-value of 0.018 indicates that model M2, with A1 (experience of being late due to bus delay) as the predictor variable, fits the data significantly better than a model with no predictors. The first threshold estimate (B8 =1) is -1.526. The significant *p*-value (<.001) suggests a clear distinction between those who are unlikely to use micro-mobility when fees are low and those who are likely or very likely to use it. The second threshold estimate (B8 =2) is 0.081 and is not statistically significant (*p*-value = 0.684). In Model M3, the Wald statistic (6.333) for A5 with a *p*-value of 0.012 indicates that this model, including the predictor variable A5 (overcrowding experience), fits the data significantly better than a model with no predictors. The interpretation of the threshold

coefficients in model M3 remains consistent with that of model M2.

The Wald statistic (6.520) for A4 with a *p*-value of 0.011 indicates that model M4, including the predictor variable A4 (travel time experience), fits the data significantly better than a model with no predictors. The significant threshold estimates for both (B5 = 1) (-3.097, *p*-value < .001) and (B5 = 2)(-1.053, *p*-value < .001) indicate clear distinctions between the three categories of micro-mobility usage likelihood. In Model M5, the Wald statistic (6.329) for A6 with a p-value of 0.012 indicates that this model, including the predictor variable A6 (experienced unpleasant smells while riding the bus), fits the data significantly better than a model with no predictors. The interpretation of the threshold coefficients in model M5 remains consistent with that of model M4.

Discussion

Riding a bus within a campus area offers affordable and sustainable transportation options. Nevertheless, the bus services provided on campus occasionally result in negative experiences for students. Our study affirms this finding, revealing that most UKM's respondents have experienced prolonged waiting times at bus stops and travel times that exceeded their expectations. The positive utility of travel diminishes as waiting/travel times go beyond the maximum acceptable or tolerable limits (21). Comparable situations have been reported elsewhere, with studies suggesting that unreliability in bus service is responsible for university students arriving late

to their classes (5). General sources of trip time variability in bus services are driver behaviour, traffic conditions, dwell time and headway (22). Prior studies, however, have frequently overlooked to consider the impacts and opportunities arising from negative bus experiences for university students. This study addressed this gap by empirically investigating the likelihood of unhappy bus riders shifting to micromobility solutions when adoption barriers are dismissed.

Through ordinal regression analysis of nine micromobility usage scenarios, this study discovered that unhappy bus riders among UKM's respondents are more likely to use micro-mobility in three specific situations: i) when usage fees are low, ii) when safety gear is optional, and iii) when access of micro-mobility is granted simply by scanning a student card.

In Model M1, experiencing bus delays is positively and significantly associated with an increased likelihood of micro-mobility use when fees are low (coefficient = 0.565, odds ratio = 1.76). This indicates that unhappy bus riders who experience delays are 1.76 times more likely to use micromobility than those who do not. The finding regarding low fees aligns with previous research that identifies cost as one of the critical factors in attracting shared riders (13). Additionally, the full potential of shared micro-mobility services can be reached by either decreasing their prices or increasing their fleet size (23).

In Model M3, the negative coefficient (-0.727) for experiencing bus overcrowding (A5=0) suggests that unhappy bus riders are less likely to view optional safety gear positively. Consequently, they have approximately half the odds of intending to use micro-mobility compared to students who have not experienced overcrowding, as indicated by the corresponding odds ratio of 0.48 (=exp(-0.727)).

While the model M3 revealed that the association between overcrowding experiences and a preference for optional safety gear is statistically significant, it underscores the need to further explore the role of individual risk tolerance in understanding this relationship. Unlike previous studies emphasising safety as paramount (24), our respondents seem more tolerant of optional safety gear when using micro-mobility. This finding aligns with previous studies indicating that young Malaysians view wearing safety helmets while riding to be trivial. This attitude persists despite their awareness that properly wearing a helmet significantly reduces the risk of fatalities and injuries in the event of a road accident (25, 26). Nevertheless, this emerging pattern warrants serious attention, given that Spain's accident records show that nearly 10% of single micromobility crashes result in serious injuries or fatalities (27). The increased speeds of micromobility vehicles, especially those modified, exacerbate safety worries even more.

Shared micro-mobility services frequently depend on app-based platforms, which may restrict access for students lacking internet connectivity. Micromobility providers can offer alternative access options to promote inclusivity, such as accepting student cards. Our regression analysis, specifically models M4 and M5, indicates that students with negative experiences on buses, such as facing unexpected delays (A4) or feeling uncomfortable (A6), are more likely to use micro-mobility in the future when access requires only a student card (B5). Model M4 reveals that students who experienced longer-than-expected bus travel times (A4=0) are 2.13 (=exp (0.565)) times more likely to use micro-mobility than those who have not experienced such delays. Meanwhile, Model M5 reveals that students bothered by unpleasant smells while travelling on campus buses (A6=0) have approximately twice the odds of intending to use micro-mobility compared to students without such experiences. Providing flexible access options could attract new users who might not have previously considered micro-mobility for short trips, for example, inside the campus area (28). Four ordinal logit models developed in this study

suggest that university students may be willing to change their travel behaviour if presented with a suitable alternative, indicating a potential decrease in loyalty to their current transportation modes. Theoretically, these behavioural changes are moderated by both the hedonic motivation of micro-mobility and the drawbacks of their current transportation choices. Based on these findings, a mobility planning division at a university should prioritise the construction of dedicated micromobility lanes, offer affordable fees or charges for shared micro-mobility and provide convenient facilities to encourage greater student adoption. Successful initiatives in two European cities; Munich and Nicosia, indicate effectiveness of these strategies in actively involving the younger population with micro-mobility solutions (29, 30).

Conclusion

Campus buses play a crucial role in offering costeffective transportation within university campuses. However, since Gen Z students, who are highly sensitive to service quality, are the primary users of these buses, any inconsistencies in service can result in frustration and a preference for other transportation options. The rising popularity of micro-mobility, driven by factors like aesthetic design, improved battery technologies, and accessibility, presents a potential solution for students dissatisfied with campus bus services.

This study explored the willingness of unhappy bus riders to use micro-mobility in the future by analysing nine possible barriers to adoption. By conducting Chi-square independence tests, we identified four main experiences linked to the inclination to use micro-mobility. We then proposed four separate ordinal logit models, each using different negative bus experiences as predictors. These single-factor logit models allowed us to estimate the likelihood of micromobility use under different circumstances. For example, according to model M2, students who have experienced being late to class due to bus delays are 1.76 times more likely to consider using micro-mobility when it is easily accessible with a student card.

Students' willingness to use micro-mobility options reflects early support for making their campus greener and more sustainable. This finding is encouraging for university transport policymakers who want to promote the adoption of micro-mobility. However, it is crucial to address the barriers related to varied access options, student friendly pricing plans and safety, otherwise micro-mobility programs on campus may struggle to make an impact on sustainability (31). While integrating micro-mobility may require additional investment in infrastructure, facilities, and awareness campaigns, a potential solution lies in public-private partnerships.

Future studies could enhance the generalizability of these findings by expanding the scope of the study to include surveys at other local universities with similar transportation contexts. A larger sample size would further validate the parameter estimates in our ordinal logit regression models. Additionally, exploring the causal relationships underlying the observed associations could provide deeper insights into the factors driving micro-mobility adoption. Moderated mediation analyses could help identify intermediate variables explaining these relationships or other factors influencing their strength and direction.

By addressing the limitations of current campus bus services and actively promoting micromobility options, universities can create a more efficient, sustainable, and student-friendly transportation environment.

Abbreviation

UKM: National University of Malaysia.

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Author Contributions

Amirul: Conceptualized the study, collected the data, and wrote the first draft of the article, Haniff: Contributed substantially to the methodology and formal analysis, critically revised the draft, provided supervision, endorsed the article for submission and responded to corrections.

Conflict of Interest

The authors agree that this research was conducted without self-benefits or commercial or financial conflicts.

Ethics approval

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640