Understanding Micro-Mobility Hub Adoption

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SHORT SUMMARY

Micro-mobility emerges as a promising solution for reducing car dependency in urban environments, providing an alternative and environmentally friendly way of commuting. This study investigates individuals' preferences for using micro-mobility modes within a micro-hub-based mobility system and identifies the behavioural and attitudinal factors influencing their adoption. A survey with stated preference experiments was distributed in the United Kingdom, resulting in 500 responses. A Hybrid Choice Model with two latent variables, representing digital comfort and perceived micro-mobility hub attractiveness, was estimated and provided significant insights into individuals' choice behaviour. Results show that waiting time, helmet provision, charging level, and contextual conditions such as weather and bicycle lane coverage significantly influence individuals' final choice. Finally, digital comfort and micro-hub perceived attractiveness significantly influence commuters' behaviour, with higher digital comfort and more positive perceptions of micro-mobility hubs exhibiting a greater propensity to adopt micro-mobility services.

Keywords: Discrete choice modelling, Micro-mobility, Multi-modal transport, Shared mobility, Urban mobility.

1. INTRODUCTION

A mobility hub is a clearly identifiable area where different public and shared transport modes are brought together and connected, to increase accessibility and improve users' experience (CoMoUK, 2019). We extend this concept to micro-mobility hubs, which are defined as designated and permanent areas that integrate shared micro-mobility services with public transport (PT). Unlike mobility hubs, we consider micro-mobility hubs placing emphasis on first- and last-mile connectivity and short distance trips, contributing to efforts towards reducing car dependency and improving PT access.

Although micro-mobility hubs share similarities with conventional mobility hubs, they serve distinct functions by prioritizing short trips and first- and last-mile connectivity. Despite this distinction, the planning, integration, and perception of micro-mobility hubs as a standalone concept remain largely unexplored, as they are often considered merely a component of broader mobility hub systems.

This study examines the planning and user-oriented dimensions of micro-mobility hubs through the estimation of a Hybrid Mixed Multinomial Logit (MMNL) model, incorporating both survey data and real-world contextual factors. The results provide insights into how infrastructure, safety, and user characteristics jointly influence the adoption of micro-mobility hubs, as well as users' preferences and trade-offs relevant to the design and implementation of micro-mobility hubs.

2. METHODOLOGY

The survey included questions on socio-demographics, travel behaviour, micro-mobility familiarity, attitudes towards hub development, and discrete choice experiments. The survey was distributed in the United Kingdom, resulting in 500 responses. Quotas based on age, gender, region, and income ensured a representative sample. The SP experiment was designed to examine individuals' preferences and trade-offs regarding the potential implementation of micro-mobility hubs at their area of living. The data were analyzed descriptively and used to estimate a Hybrid Mixed Multinomial Logit (MMNL) model, with two distinct latent variables, using R and the Apollo choice modelling package (Hess and Palma, 2019). Table 1 presents the attributes and the levels of the SP experiment, while Figure 1 displays an example of the choice experiment.

Additional contextual variables were used to capture real area-level characteristics. Official UK administrative boundaries were used (Office for National Statistics, 2024a, 2024b), alongside OpenStreetMap data that were extracted via Overpass-Turbo (OpenStreetMap contributors, 2026). Cycling infrastructure density was calculated as the ratio of total bike lane length to area size (km/km2), while crash data were obtained from official national statistics (UK Department for Transport, 2025) and aggregated at regional level. Figure 2 illustrates the overall methodological workflow adopted in this study.

Table 1: Stated Preference Experimental Design Attributes and Levels

Attribute	**Levels**
Available mode options	*Micro-car, E-bicycle, E-scooter, E-moped, None of the above*
Waiting Time	*Right Away, 5-10-15 minutes*
Travel Time	*5-7-10-12-15-17-20-22-25-27-30-35 minutes*
Walking Time to final destination	*2-5-7-10-15 minutes*
Cost	*0.5-1-2-3-4-5 euros*
Bike lane	*100%-80%-60%-40%-30%-0% of trip, Not applicable*
Charging level	
Additional features	*Helmet, SOS button, Sharing, None*
Additional Provided information	
Trip purpose	*Shopping, Leisure, Work, Education, Errands, Visiting a city*
Weather condition	*Sunny and warm, Sunny and cold, Rainy but warm, Rainy and cold, Snow*
Area speed limit	*30km/hr, 40km/hr, 50km/hr*



Figure 1: Stated preference experiment

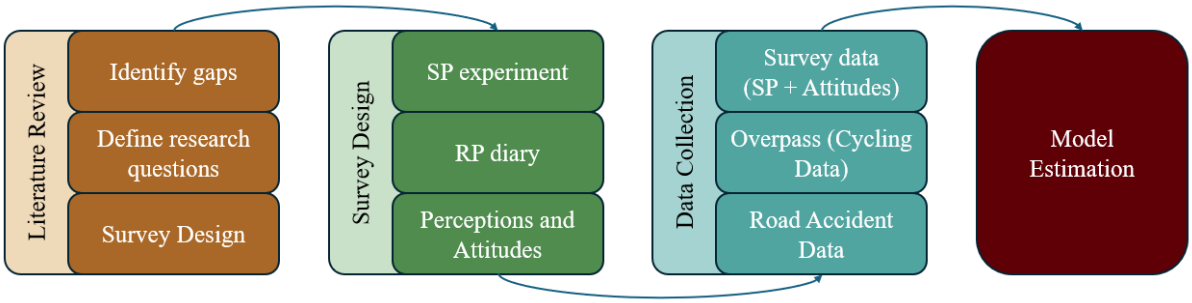


Figure 2: Methodological Workflow

3. RESULTS AND DISCUSSION

Descriptive Analysis

The final sample was balanced in terms of gender (50.6% female, 49.4% male), while the age distribution was relatively even across groups, with the largest share of participants belonging to the 25–34 age group (26.3%). Participants were drawn from all regions of the United Kingdom. Most respondents were employed (71.7%), while 6.4% were students, and the sample was relatively well educated, with more than 53.0% holding a university degree or higher qualification. Additionally, 64.7% reported engaging in physical activity for several hours per week.

Respondents reported moderate levels of perceived knowledge about micro-mobility (3.4) and micro-mobility hubs (3.0) on a six-point scale. To complement these self-reported assessments, the survey included a factual quiz on micro-mobility regulations and definitions, covering topics such as maximum legal speed limits. A penalized knowledge score was constructed by assigning +1 for each correct response and −1 for incorrect responses, with negative values truncated at zero. The resulting score (0–4) was subsequently rescaled to a six-point scale for comparability with the perception indicators. The average score was 2.2 out of 6, revealing a notable gap between perceived and actual knowledge. This finding highlights the need for awareness campaigns and educational initiatives.

Attitudinal indicators suggest generally positive perceptions of micro-mobility hubs, particularly regarding their potential contribution to environmental, reduced parking demand, and improved accessibility and connectivity. Finally, the digital familiarity indicators show that respondents are generally comfortable with smartphone use, particularly for social media, mobility navigation apps, and digital payments.

Table 2: Descriptives of travel behaviour, knowledge, and attitudinal indicators

Variable	Min	Max	Mean	SD
Perception of knowledge (6-point) and knowledge score (0-4 → Rescaled 6-point)				
Perception: micro-mobility knowledge	1	6	3.4	1.6
Perception: micro-mobility hub knowledge	1	6	3.0	1.6
Knowledge score	1	6	2.2	1.4
Micro-hub Perceived Attractiveness				
It would strengthen the local community's economy	1	6	4.5	1.1
It would enhance the environmental sustainability of the area	2	6	4.8	1.0
It would contribute to reducing the need for parking spaces	1	6	4.7	1.1
It would improve the safety of pedestrians and cyclists	1	6	4.5	1.2
It would enhance accessibility & connectivity with other modes	2	6	4.7	1.0
Digital comfort				
I use my phone for work purposes	1	6	3.9	1.8
I use my phone for payments	1	6	4.6	1.6
I use social media	1	6	5.0	1.4
Learning new technologies is often hard for me	1	6	2.8	1.5
I use mobility navigation apps	1	6	4.7	1.2
I prefer using delivery lockers	1	6	3.2	1.7

Discrete Choice Modeling

Following the descriptive analysis, a Mixed Multinomial Logit (MMNL) model was specified and estimated. Five utility functions were defined as corresponding to the alternatives micro-car,

e-bicycle, e-scooter, e-moped, and the option to continue using the respondent's usual travel mode. Respondents were asked to choose among four micro-mobility alternatives: micro-car, e-bicycle, e-scooter, and e-moped. A panel error component was included to account for repeated observations per individual. Additional error components across alternatives were tested, but only the error component between e-bicycles and e-scooters was retained.

The conceptual framework of the Hybrid Choice Model used in this study is shown in Figure 3. The model integrates context factors and level of service characteristics, obtained by the SP experiment, with demographics, and two latent variables capturing digital comfort and perceived micro-mobility hub attractiveness. These two latent variables are measured through different sets of attitudinal indicators and linked to specific socio-demographic characteristics, and contextual variables derived from real-world data.

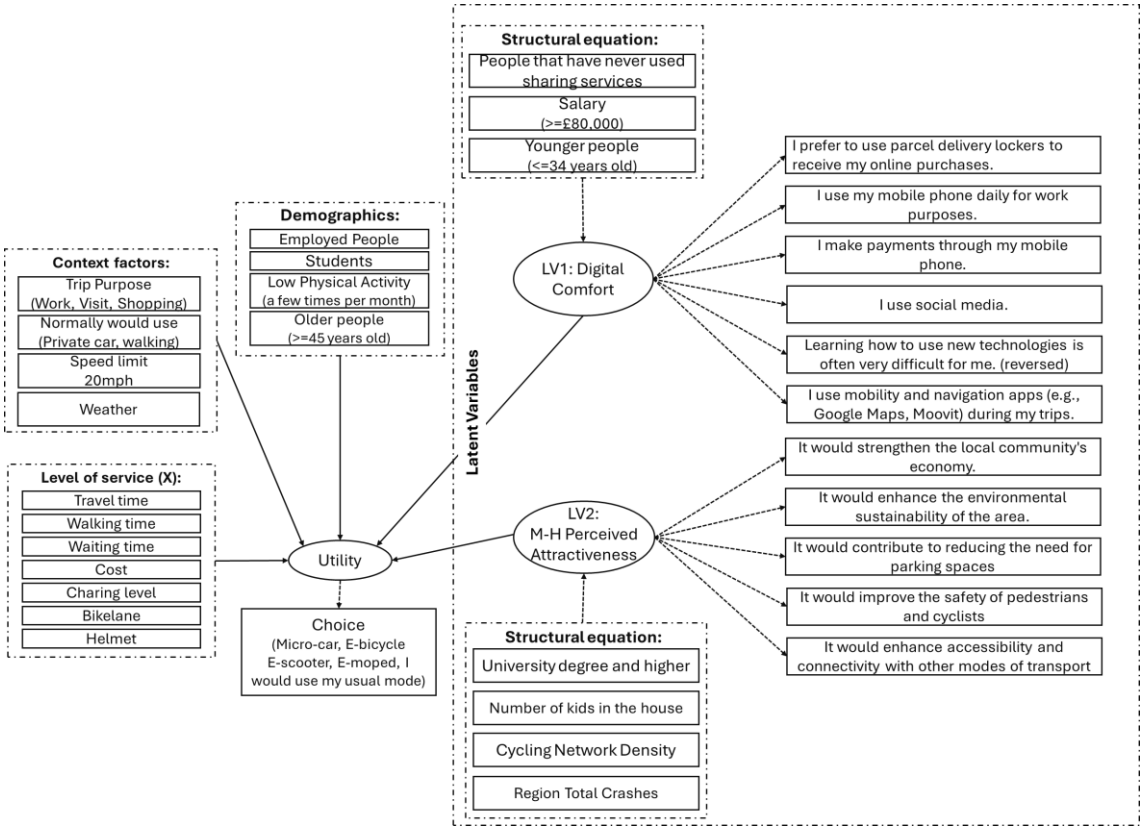


Figure 3: Hybrid Choice Model Modeling Framework

Table 3 presents the estimation results of the Hybrid MMNL model, demonstrating a satisfactory model fit with strong explanatory power, with an adjusted rho-square of 0.25. The alternative-specific constants (ASCs) provide insights into the baseline preferences for each travel option relative to the reference alternative (usual mode). More specifically, as shown in Table 3, e-bicycles (β=-2.077, t=-4.51), e-scooters (β=-3.050, t=-5.94), and e-mopeds (β=-2.399, t=-4.83) are negative and statistically significant, indicating a lower inherent preference for these options. In contrast, ASC for micro-cars is positive but not statistically significant, suggesting no clear baseline preference.

In addition, waiting time (β=-0.031, t=-4.12), walking time to the final destination (β=-0.014, t=-1.47), and cost negatively affect the attractiveness of the micro-mobility alternatives.

Furthermore, the provision of helmet (β=0.139, t=3.33) can mitigate the negative effect of cost on the attractiveness of e-bicycles, e-scooters and e-mopeds. Travel Time exhibits the expected negative trend but lacks statistical significance implying that its impact is limited in this case. Moreover, the interaction term between travel time and bike lane coverage for e-bicycles is positive (β=0.017 t=1.40), suggesting that better cycling infrastructure partially mitigates the disutility of travel time. However, this effect is statistically significant at only the 80% confidence level. Additionally, the interaction term between travel time and sunny weather conditions for the different micro-vehicle varies. For e-bicycles, the effect is positive and statistically significant (β=0.027, t=2.13), suggesting that favorable weather conditions reduce sensitivity to travel time. The corresponding effects for e-scooters (β=0.019, t=1.34) and e-mopeds (β=0.025, t=1.73) are positive and statistical significant at the 80% and 90% confidence levels, respectively, indicating weaker evidence of this pattern. For micro-cars, the effect is negative and not significant (β=-0.013, t=-1.17), suggesting no clear moderating role of weather. These results highlight that infrastructure, and contextual conditions do not only directly affect mode choice but also shape how users perceive travel effort.

Travel purpose also influences mode choice and micro-vehicles attractiveness, with work-related trips (β = 0.474, t = 1.61), and shopping trips (β = 0.366, t = 1.65), showing positive and marginally significant effects across all micro-vehicles. In contrast, visiting another city has a stronger and statistically significant effect for micro-cars (β = 0.517, t = 2.52) and e-bicycles (β = 0.680, t = 2.77), highlighting the potential of micro-hubs as a viable option for tourists and visitors. Charging level has a positive and statistically significant effect (β = 0.238, t = 4.13), suggesting that battery availability is mostly considered for e-scooters and e-mopeds playing a key role in enhancing their attractiveness.

Habitual mode choice plays an important role in influencing micro-vehicles usage. When a trip was meant to be performed normally using a private car, micro-cars show a statistical significant increase in their attractiveness (β = 0.744, t = 4.02). This highlights the importance of considering micro-cars in efforts to reduce conventional private car dependency and to shift people towards smaller and more sustainable mobility options. For e-bicycles and e-scooters attractiveness increased when trips would otherwise be performed on foot, suggesting that these modes may substitute walking.

Additionally, a positive and marginally significant effect of the micro-mobility knowledge score (β = 0.209, t = 1.72), suggests that individuals with greater understanding of micro-mobility are more likely to adopt e-bicycles. Students show a higher likelihood of choosing e-bicycles and e-scooters (β = 0.703, t = 1.62). Older individuals are more likely to retain their usual travel mode (β = 0.638, t = 2.12), while physical inactivity shows a positive but non-significant effect (β = 0.570, t = 1.44) on avoiding micro-mobility options. In contrast, employed individuals are more likely to utilize the micro-mobility hub (β = -0.504, t = 1.58).

Finally, perceived hub attractiveness plays a significant role in shaping mode choice (β = 0.649, t = 4.17), whereas digital comfort, although positively signed does not reach conventional levels of statistical significance (β = 0.222, t = 1.32), suggesting that attitudinal perceptions of infrastructure outweigh digital familiarity. This suggests that attitudinal perceptions of the system itself play a more decisive role than digital familiarity, indicating that improving how micro-mobility hubs are perceived may be more effective than focusing solely on technological readiness.

Table 4: Model Estimation

Variables	Coef.	T-ratio
ASC_Microcar (MC)	0.244	0.582

ASC_Ebicycle (EB)	-2.077	-4.51
ASC_Escooter (ES)	-3.050	-5.94
ASC_Emoped (EM)	-2.399	-4.83
ASC_UsualMode (UM)	-	-
Generic to MC, EB, ES, and EM		
Waiting Time	-0.031	-4.12
Walking Time	-0.014	-1.47
Travel Purpose: Work	0.474	1.61
Travel Purpose: Shopping	0.366	1.65
Generic to EB, ES and EM		
Provision of Helmet x Cost	0.139	3.33
Generic to MC and EM		
Travel Time	-0.007	-0.79
Generic to EB and ES		
Travel Time	-0.008	-0.77
Cost	-0.053	-1.10
Students	0.703	1.62
Generic to ES and EM		
Charging Level	0.238	4.13
MC		
Travel Time x Sunny Weather	-0.013	-1.17
Cost	-0.077	-1.66
Travel Purpose: Visit City	0.517	2.52
Mode that would normally use in this scenario Specific: Private Car	0.744	4.02
Mode that would normally use in this scenario Specific: On foot	-0.377	-1.61
EB		
Travel Purpose: Visit City	0.680	2.77
Speed Limit equals 20mph	0.545	2.70
Travel Time x Sunny Weather	0.027	2.13
Travel Time x Bikelane Coverage	0.017	1.40
Mode that would normally use in this scenario Specific: On foot	1.122	4.35
Micro-mobility Knowledge score	0.209	1.72
ES		
Travel Time x Sunny Weather	0.019	1.34
Mode that would normally use in this scenario Specific: On foot	0.983	3.31
EM		
Cost	-0.164	-2.18
Travel Time x Sunny Weather	0.025	1.73
I would use my usual mode		
Age (Older than 45 years old)	0.638	2.12
Physical Activity (Less often or never)	0.570	1.44
Employed People	-0.504	-1.58
Latent Variables: Generic On MC, EB, ES, EM		
Digital Comfort	0.222	1.32
Perceived Hub Attractiveness	0.649	4.17
Error Terms		
Panel error	1.396	15.02
Error Comp. (EB&ES)	0.4531	2.00
Structural Equations of Latent Variables		
<u>Digital Comfort</u>		
Younger people (<=34 years old)	0.668	4.94
Yearly Salary (>=£80,000)	0.513	3.19
Never Used a Sharing Scheme Before	-0.567	-4.17
<u>Perceived Hub Attractiveness</u>		

Number of kids in the household	0.195	3.43
Higher education (University degree and above)	0.394	3.29
Total number of crashes	-0.264	-2.53
Cycling Network Density	1.088	2.33
Measurement Model		
Digital Comfort		
I use my phone for work purposes	1.058	7.95
I use my phone for payments	2.388	6.84
I use social media	1.643	7.75
Learning new technologies is often hard for me (Reversed)	0.202	1.93
I use mobility navigation apps	1.720	8.23
I prefer using delivery lockers	0.786	6.70
Perceived Hub Attractiveness		
It would strengthen the local community's economy	2.441	10.44
It would enhance the environmental sustainability of the area	2.842	9.38
It would contribute to reducing the need for parking spaces	2.393	10.01
It would improve the safety of pedestrians and cyclists	2.062	10.40
It would enhance accessibility & connectivity with other modes	2.587	9.97
Adj.Rho-squared vs equal shares	0.25	
LL at equal shares, LL (0)	-8434.1	
LL (final)	-6675.04	
Observations	1387	

The structural equations of the two latent variables provide additional significance insights into the factors shaping individuals' attitudes. Digital comfort is positively associated with younger ages ($\beta = 0.668$, $t = 4.94$) and higher income levels ($\beta = 0.513$, $t = 3.19$), while individuals who never used a sharing service exhibit significantly lower levels of digital comfort ($\beta = -0.567$, $t = -4.17$).

Perceived hub attractiveness is positively influenced by the number of children in the household ($\beta = 0.195$, $t = 3.43$), higher education levels ($\beta = 0.394$, $t = 3.29$) and more dense cycling networks ($\beta = 1.088$, $t = 2.33$). In contrast, higher crash levels are associated with lower perceived attractiveness ($\beta = -0.264$, $t = -2.53$). An alternative specification using cycling-specific crashes yielded similar results, and for these total crashes were retained to better capture overall traffic safety conditions.

4. CONCLUSIONS

The results show that service attributes, infrastructure, and safety conditions significantly influence micro-mobility hub adoption. Micro-cars are more likely to substitute private car trips, while e-bikes and e-scooters tend to replace walking. Perceived hub attractiveness plays a key role, highlighting the importance of infrastructure and safety improvements. These findings suggest that policy efforts should focus on improving cycling infrastructure and enhancing safety conditions, as well as increasing the perceived attractiveness of micro-mobility hubs through targeted design and communication strategies. Limitations include the use of stated preference data and a single-country context. Future research should incorporate real-world data and extend the analysis across countries.

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