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Attitudinal profiles of potential shared cargo bike users in Budapest

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Abstract

Shared cargo bike systems offer a practical and promising alternative for short-distance urban trips, especially where cars dominate last-mile delivery and household travel. Yet, their adoption across most of the European continent remains limited and highly context dependent. Understanding the profiles of potential users is essential for designing targeted interventions that promote uptake. Hence, this study draws on survey data from 941 respondents across Budapest to segment potential users. Using Latent Class Cluster Analysis, this study explores the heterogeneity of urban travelers' attitudinal profiles, identifying how these variations shape their openness to adopting shared cargo bike services. Based on the analysis, 6 clusters are identified: disengaged, sceptics, indifferent, explorers, supporters, and enthusiasts. While middle-aged individuals are almost evenly distributed across clusters, older respondents are mainly disengaged or sceptics, and younger adults show a higher concentration in the indifferent cluster. Car users are predominantly found among sceptics, whereas multimodal individuals or cyclists are typically supporters or enthusiasts. By integrating segmentation which includes attitudinal factors, this study informs targeted strategies for shared cargo bike uptake and offers insights that support sustainable mobility transitions in other urban contexts.

Keywords Shared cargo bike, Attitudes, Heterogeneity, Latent class cluster analysis, Adoption

1 Introduction

Cities aim to reduce car dependency and emissions, still last-mile delivery and individual mobility are dominated by cars [19]. Shared cargo bikes (SCB) have emerged as a sustainable alternative, offering both functional capacity and environmental benefits, but their introduction into everyday mobility systems has been slow and uneven [33]. Evidence shows that cargo bike sharing can displace

car use and even reduce car ownership [1], but results depend on user motives and perceived performance.

Recent research has documented the potential of electric cargo bikes and shared cargo bikes, and highlighted their capacity, range, and environmental benefits [5], but also pointed to cost, infrastructure, and social acceptance as persistent constraints [33]. Adoption of SCB remains in its early stages and varies strongly across cities, depending on local conditions such as infrastructure, mobility systems, and socio-economic characteristics, with user openness closely tied to personal travel habits. Motivations, such as saving money, maintaining an active lifestyle, and reducing carbon footprint, align with earlier findings on e-cargo bike adoption, where lower cost, health gains, and eco-consciousness play a central role [1]. At the same time, users continue to see clear disadvantages, as cargo bikes are often viewed as inferior to

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cars in terms of safety, speed, weather protection, and comfort [22].

The demographic profile of early adopters is relatively consistent, often described as upper-middle income, well-educated middle-aged men, frequently with children and a pro-cycling outlook [12, 18, 22]. However, evidence suggests that sharing schemes can reach beyond this group. Compared to private cargo bike ownership, SCB in Europe attract more young adults and car-free households, pointing to their potential to broaden access for those who might not engage with cargo bikes [23]. This shift underlines the relevance of shared systems in diversifying user base and fostering inclusivity in sustainable transport.

Behavioral research demonstrates that the adoption of new mobility options is shaped less by technical operations and more by perceptions [9, 33]. Broader mobility research highlights attitudes, identity, and risk perception as core drivers for the shared service uptake [16]. Segmentation methods reveal why populations respond differently to the same service by uncovering heterogeneous perceptions and barriers [8, 18]. Yet this approach has rarely been applied to potential SCB users before system deployment, as most studies focus on existing users or operational outcomes.

This leaves a knowledge gap on pre-deployment attitudinal diversity, which this study addresses by examining the heterogeneity of potential SCB users in Budapest. Moreover, directly comparable evidence on mobility-habits and shared mobility adoption profiles in Budapest remains limited, which further supports the need for an exploratory segmentation approach. This attitudinal diversity is important because, before a shared cargo bike system is available, potential users evaluate a service that remains hypothetical in the local context. At this stage, attitudes are shaped mainly by expectations, perceived compatibility, perceived risk, and indirect knowledge rather than by the visible presence of the service [14, 24]. Once a system is deployed, even individuals who have not used it may evaluate it differently as they can observe the service, assess its locations, and see how it fits into everyday practice. Research shows that attitudes and behavior are interrelated and may change as people gain more information about transport options [16]. For shared cargo bike systems, which are still absent in many cities, including Budapest, studying pre-deployment attitudinal profiles is useful for identifying diverse attitudinal groups before implementation and for designing targeted introduction strategies [33]. Latent class cluster analysis (LCCA) is employed on attitudinal data grounded in the Diffusion of Innovation (DOI) framework to uncover distinct attitudinal segments. Compared to traditional clustering techniques, LCCA provides a model-based framework that allows for probabilistic classification and formal model selection, making it particularly suitable for

identifying latent attitudinal segments [29]. The composition of each group is described, their attitudinal patterns are examined, and insights are discussed in relation to targeted policy to support effective adoption.

The paper is structured as follows. The next section reviews the relevant literature and theoretical background. This is followed by the methodology section describing the survey design, data collection, and analytical approach. The results section presents the factor analysis and latent class segmentation outcomes. Finally, the discussion and conclusion sections interpret the findings and outline implications for policy and future research.

2 Literature review

A recurring finding in cargo bike studies is that adoption is not primarily limited by the technical feasibility of moving goods by bike, but by how people perceive this new alternative transport mode. Even when the functional capacity of cargo bikes is acknowledged, perceived disadvantages compared to the car, such as safety, speed, weather protection, and comfort, remain salient in user evaluations [22]. Infrastructure conditions amplify these perceptions, where cycling environments feel unsafe or stressful, the practical viability of cargo bikes is undermined regardless of potential benefits [33]. In addition, service design can either reduce or reinforce perceived effort. Many SCB schemes operate with limited fleets or community-oriented models, which restrict availability and increase coordination costs for users. Scaling up is therefore tied to lowering friction through improved access, coverage, and integration into mainstream mobility platforms [33].

Who adopts SCB services in particular, appears systematically patterned. Early adopters have been described as relatively well-educated, higher-income, middle-aged men in households with children, who already hold a pro-cycling outlook [12, 18, 22]. At the same time, evidence indicates that shared systems can broaden participation beyond the classic users, where SCB may attract more young adults and car-free households, suggesting a pathway for expanding access to cargo capacity without requiring ownership or storage space [23]. These observations reinforce two points, namely SCB adoption is driven by subjective evaluations rather than by a single universal cost-benefit calculation, and these evaluations vary across population groups [16, 33].

Although shared cargo bikes belong to the broader field of shared micromobility, their adoption differs from shared bikes, e-bikes, and e-scooters because they are more strongly linked to task-specific travel, such as carrying goods, transporting children, or replacing selected car trips. In contrast, shared bikes and e-scooters are often associated with commuting, first- and last-mile connections, and leisure travel. Recent research on shared cargo bike systems also shows that their adoption and upscaling depend not only on individual willingness, but also on

availability, infrastructure, service organization, and integration into the wider urban mobility regime [33]. Previous studies on shared micromobility users show that adoption is heterogeneous and often varies by age, income, car access, mobility habits, experience, motivation, trip purpose, and the urban form of the residential area [2]. Latent class and segmentation studies further confirm this heterogeneity. For example, Geržinič et al., [9] identified six adoption-attitude profiles for shared micromobility integration with public transport: progressives, bold innovators, hesitant participants, skilled sceptics, conservatives, and anxious observers. Jena et al., [15] classified e-scooter users into *Joyriders* and *Busyriders* according to trip frequency, motivation, and purpose, while Fu et al., [8] identified different multimodal travel patterns among users across Utrecht and Rotterdam, based on the frequency of different mode use and travel contexts. These studies show that shared micromobility adoption is structured around different levels of openness, perceived barriers, mobility routines, and use motivations rather than forming a single homogeneous user group.

To capture how potential users evaluate SCB services before they exist, the Diffusion of Innovation (DOI) framework offers a direct link between perceived attributes of an innovation and readiness to adopt it [14, 24]. DOI is particularly suitable for SCB because many potential adopters have limited direct experience with cargo bikes, making perceptions of fit, visibility, and try-out opportunities especially consequential [33]. The most commonly used DOI attributes in mobility contexts include relative advantage (RA), compatibility (CP), complexity (CM), trialability (TR), and observability (OB), and can be mapped onto known barriers and facilitators from the SCB literature [14, 24].

Within the DOI perspective, *RA* reflects whether an SCB service is perceived to outperform existing options, making it a core driver of favorable attitudes [14, 33]. Survey evidence from users suggests that cargo bikes can be rated superior on many motives, but if cargo bikes are perceived as inferior to cars in safety, speed, weather protection, and comfort, the perceived advantage can quickly erode [22].

CP is central because cargo bike use is often task-specific, and this is even more pronounced in sharing systems. The innovation must fit daily routines, spatial constraints, and trip purposes, not just general travel preferences. In e-cargo bike sharing contexts, functional perceptions emerge as key differentiators between those who consider using the service and those who do not [12]. *CP* also may interact with mobility identity and existing routines, where travelers who already integrate multiple modes may perceive cargo bike sharing as a natural extension, whereas car-reliant routines may reduce perceived fit [8, 23].

CM, sometimes expressed as ease of use (*EU*), matters in SCB contexts where people must feel confident operating a larger bicycle and navigating traffic conditions, not just understand the concept [12, 14]. The built environment and service design shape perception, where protected infrastructure and ease of booking and access can reduce perceived effort and make SCB feel more usable for everyday tasks [6, 33].

TR is particularly relevant for SCB because potential users often have limited experience with cargo bikes and may find it difficult to evaluate how they would use them in everyday travel situations. The opportunity to experiment with the innovation before committing allows individuals to understand both its practical uses and operational demands. In contexts where riding a cargo bike in traffic is unfamiliar, the possibility to try a shared bike with low commitment becomes an important precondition for later adoption [14, 24].

OB matters because visibility can normalize an innovation and reduce uncertainty about social acceptability. SCB niche status partly reflects limited presence in everyday streetscapes, so when the service is not visible, it is harder for potential users to form concrete expectations or imagine use cases [33]. In adoption-attitude studies of shared micromobility, visibility and social cues repeatedly emerge as mechanisms through which willingness can shift, even when baseline attitudes differ across groups [9].

It is important that value alignment has been shown to be salient in SCB contexts, where users weigh not only practicality but also what the mode represents (e.g., environmental consciousness, lifestyle, and identity). Evidence, that cargo bike sharing users rate cargo bikes favorably on several motives, indicates that perceived value is more than an abstract “green preference”, so it can be tied to concrete mobility trade-offs [1, 16]. Likewise, motivational segmentation demonstrates that people differ in the reasons they use cargo bikes, implying that value is not homogeneous even among users [18]. A key implication of applying DOI in the SCB context is that these constructs should not be assumed to operate uniformly. In practice, DOI attributes are filtered through prior habits and risk perceptions, which vary across different groups [16, 33]. This motivates an explicitly heterogeneity-focused approach rather than relying on sample-average relationships.

Segmentation approaches are used in mobility research to explain why the same service triggers enthusiasm in some groups and resistance in others [8, 18]. LCCA is well-suited to this task because it identifies unobserved subgroups based on patterns in observed responses, enabling attitudinal profiles to emerge empirically rather than being imposed a priori [10]. LCCA has been used to reveal heterogeneity in adoption attitudes in related

shared-mobility contexts, including integration of shared micromobility with public transport, where distinct classes differ systematically in perceived drivers and barriers [9]. Similarly, latent class approaches have been applied to identify heterogeneity among potential early adopters in shared mobility markets, reinforcing that pre-deployment populations often contain multiple readiness levels rather than a single continuum [32].

SCB research indicates a meaningful potential for car-trip substitution, but also highlights persistent barriers linked to safety, comfort, and service accessibility, with adoption currently concentrated among particular user groups [1, 12, 22, 33]. DOI provides a theory-consistent structure for measuring how potential users appraise SCB services, yet these perceptions are expected to vary across individuals rather than forming an average pattern [14, 16]. What remains comparatively underdeveloped is pre-deployment evidence that maps this attitudinal heterogeneity into discrete groups that can be targeted with different interventions. Applying DOI-based constructs as inputs to LCCA addresses this gap by identifying distinct attitudinal profiles toward SCB services and enabling policy and service design to be tailored to the needs and constraints of each group [9, 10, 33].

3 Methodology

3.1 Data collection and survey design

A survey was conducted to assess the potential for a shared cargo bike service in Budapest. As the capital of Hungary is home to approximately 1.7 million inhabitants and already offers shared micromobility services, such as BuBi (shared bicycles) and Lime (shared e-scooters). This makes it an ideal location for examining the adoption potential of new micromobility options, like shared cargo bikes. The survey was administered via an online platform in November 2024 by a professional market research company, using quota-based sampling to align the sample with the age and gender distribution of the Budapest population. The obtained dataset was prepared for analysis by excluding incomplete and/or invalid responses, including responses with inconsistent response patterns and responses completed in less than 7 min. The 7-minute threshold was used as a quality-control criterion based on the survey length and previous testing, as shorter completion times were considered unlikely to reflect attentive reading and reliable answering. This exclusion rule was applied uniformly before the main analyses, reducing the sample from 982 responses to a final set of 941 valid responses. Respondents who did not report household income were retained in the analysis as a separate “not reported” income category. This decision was based on a sensitivity check comparing model estimation with and without this group. Since exclusion reduced the statistical power and stability of

the model estimates, the “not reported” category was included as an explicit income level rather than treating these responses as missing values.

The survey consisted of three sections. The first section gathered socio-demographic data, the second section focused on travel patterns, recording the frequency of trips made in an average week using various transport modes including private cargo bikes, while the third section employed statements derived from the DOI theory to assess attitudes toward SCB and their potential adoption. Also, mobility identity was measured with one self-reported item asking respondents to complete the statement “I personally identify as a...”. Response options were public transport user, pedestrian, cyclist, car driver, multimodal user, and other. In this study, mobility identity refers to respondents’ self-categorization with a transport-user group, rather than to observed travel frequency alone. This conceptualization follows previous work showing that travel behavior is not only a matter of habits or preferences but can also be connected to self-identity and the symbolic meaning attached to transport modes [11, 20].

Since the DOI theory posits that individuals form attitudes toward an innovation based on their perceptions of key attributes [14], the survey included statements, derived from the literature, reflecting the five core DOI constructs: relative advantage (RA) [3, 24], compatibility (CP) [4, 14], trialability (TR) [4, 27], observability (OB) [4], and complexity (Table 1). In alignment with previous research, we presented complexity in its reverse form, ease of use (EU) [4, 27], to better reflect the respondent perspectives. In addition, we incorporated items capturing perceived value (PV) [27], to account for personal and contextual relevance in adoption decisions. A 7-point Likert scale measured the level of agreement with these statements, ranging from 1 (“completely disagree”) to 7 (“completely agree”), enabling a more precise and reliable assessment.

To extract factors from the statements, an Exploratory Factor Analysis (EFA) was conducted as an iterative item-reduction procedure. Maximum likelihood extraction and oblimin rotation were used, as the attitudinal dimensions were expected to be correlated. The suitability of the data was tested using the Kaiser-Meyer-Olkin (KMO) test with higher values indicating greater appropriateness [26]. Bartlett’s test of sphericity and the determinant of the correlation matrix were also computed to confirm that the data were sufficiently correlated for factor extraction while avoiding multicollinearity. Items were evaluated based on primary factor loading, cross-loading patterns, uniqueness, and theoretical interpretability. Items that did not meet these criteria were removed stepwise, and the EFA was re-estimated after each removal until a stable and interpretable factor structure was obtained. Loadings below 0.30 were considered insufficient for item retention.

Table 1 Measurement items and associated statements

Latent variable	Statement
Relative advantage	RA1: A shared cargo bike is more efficient than other modes I currently use. RA2: A shared cargo bike is more affordable than owning a car. RA3: A shared cargo bike is a good option for replacing private car trips.
Compatibility	CP1: Riding a shared cargo bike is easily compatible with my daily mobility. CP2: A shared cargo bike is well suited to carry out my daily tasks. CP3: It is difficult for me to use a shared cargo bike according to my plans.
Trialability	TR1: I can test a cargo bike as long as possible to form an opinion about it. TR2: I have the opportunity to try a cargo bike within my circle of friends. TR3: A shared cargo bike is a good way for me to try out using a cargo bike.
Observability	OB1: Cargo bikes have noticeably changed today's transport landscape. OB2: When I use a cargo bike, it is noticed by people in my personal environment. OB3: I often notice other people using cargo bikes on the road.
Ease of use	EU1: A cargo bike is easy to operate. EU2: I am confident in using a cargo bike. EU3: A shared cargo bike is easy to rent and use.
Perceived values	PV1: A cargo bike fits with my personality. PV2: A cargo bike represents what is important to me. PV3: A cargo bike would enable me to behave according to my values.

3.2 Data analysis

Following EFA, factor scores were calculated using average sum scores. These factor values were used as inputs for the LCCA, as illustrated in the modeling framework (Fig. 1).

LCCA is a statistical approach that identifies unobserved subgroups within a sample based on shared response patterns with discrete latent variables serving as indicators [10]. The method seeks to maximize heterogeneity between clusters while maintaining homogeneity within them. The probability of observing a given response pattern is expressed in Eq. 1 [28].

$$P(y_i|z_i^{cov}) = \sum_{k=1}^K P(k|z_i^{cov}) \prod_{t=1}^6 P(y_{it}|k, z_i^{cov}) \quad (1)$$

where y_{it} represents the response of individual i to indicator t , the latent class k , consisting of K categories, serves as an unobserved variable that links the observed indicator y with the covariates z_i^{cov} . From Eq. 1 it can be noticed that LCCA involves two probability

components: the probability of the class membership model $P(k|z_i^{cov})$ and the probability of the measurement model $P(y_i|z_i^{cov})$, which means that the optimal number of classes was determined using both the indicators (factors) and the covariates (moderators).

A variety of statistical and model fit indices are available to support the LCCA model selection, including the Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC), and changes in log-likelihood [17, 31]. While AIC is widely used for evaluating model quality, seeking to minimize information loss by balancing fit and complexity, it tends to favor more complex models due to its relatively weaker penalty for additional parameters. In contrast, BIC imposes a stronger penalty on model complexity, making it particularly suitable for identifying parsimonious solutions and comparing the fit of different models with lower indices indicating better fit [30]. Nylund et al., [21] identified BIC as one of the most reliable criteria for selecting the optimal number of latent classes. Accordingly, BIC values were used as the primary criterion in this study.

4 Results

4.1 Sample characteristics

An overview of the sample characteristics is presented in Table 2. The gender distribution of the sample is nearly even with 51.01% identifying as women and 48.99% as men, which closely reflects the city's gender composition according to the Hungarian Central Statistical Office (KSH). In terms of age, the most represented group is 40–54 (33.79%), which aligns with the average age range of Budapest's population, as reported by KSH. This is further illustrated by the comparison with population statistics in Table 2, which highlights closer alignment in gender and age, while more pronounced deviations in other socio-demographic characteristics. That imbalance is characterized by a relatively high share of university-educated individuals, with 45.38% holding a university degree, while only 3.72% reported primary school as their highest level of education. The majority of participants (75.13%) are employed, whereas retired (12.75%), unemployed (5.10%) or students (4.36%) are considerably less represented.

Most respondents live in one- or two-person households (26.04% and 34.75%), while larger households comprised 16.90%. In terms of family composition, 69.18% of respondents reported having no children, while 28.16% had one or two children. Respondents with more than two children made only 2.66% of the sample. Household income was collected in Hungarian Forints and grouped into categories reflecting the general income structure in Hungary. The categorization was informed by the Hungarian Central Statistical Office (KSH) STADAT income and consumption database, including household income indicators and income-distribution statistics by income groups. Monetary

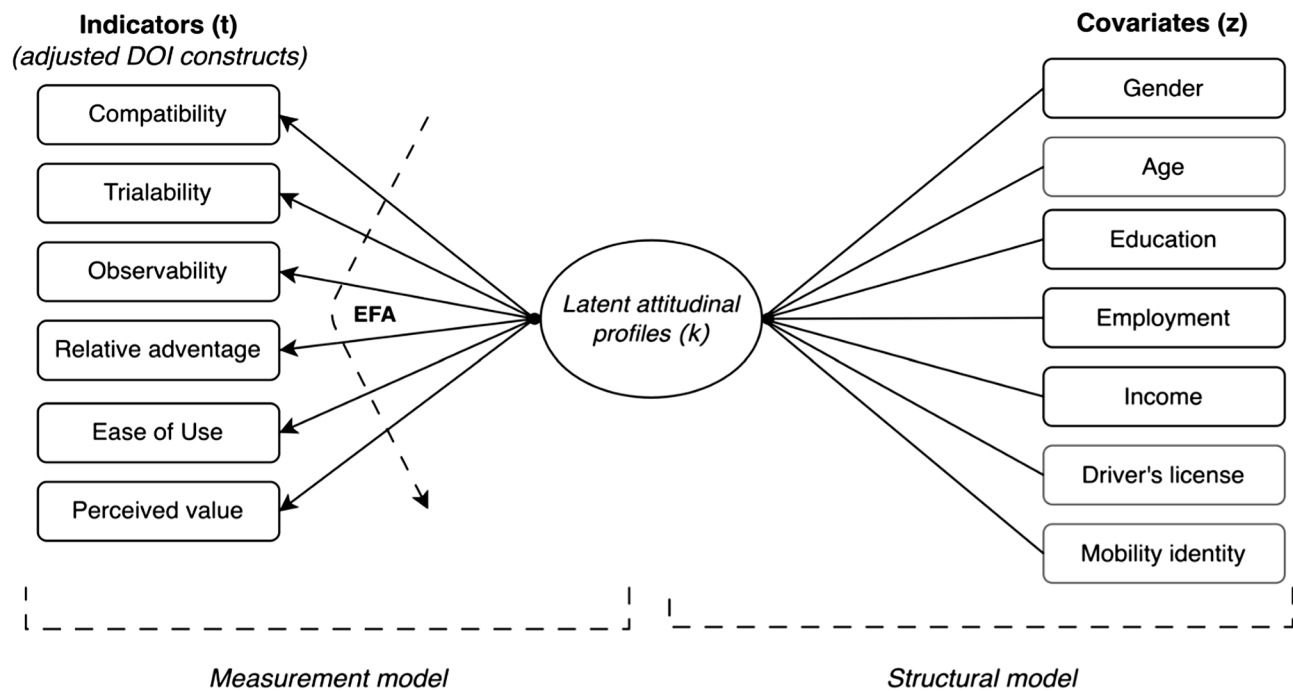


Fig. 1 Modeling framework of latent attitudinal profiles

Table 2 Socio-demographic characteristics and mobility identity of the sample

Category	Sample		Population Share	Category	Sample	
	Count	Share			Count	Share
Gender				Household number		
Man	461	48.99%	~47%	1	245	26.04%
Woman	480	51.01%	~53%	2	327	34.75%
Age				3	210	22.32%
18–24	87	9.25%	~9–10%	More than 3	159	16.90%
25–39	314	33.37%	~25–30%	Income		
40–54	318	33.79%	~25–30%	Not reported	71	7.55%
55–64	114	12.11%	~12–14%	< 875€	288	30.61%
> 64	108	11.48%	~18–22%	875€<1,875€	355	37.73%
Education				1,875€<2,500€	187	19.87%
Primary school	35	3.72%	~10–15%	≥ 2,500€	40	4.25%
High school	332	35.28%	~40–45%	Nr. of children		
Vocational	147	15.62%	~20–25%	No children	651	69.18%
University degree	427	45.38%	~25–35%	1–2 children	265	28.16%
Employment				More than 2	25	2.66%
Employed	707	75.13%	~60–70%	Driver's license		
Unemployed	48	5.10%	~3–5%	Yes	641	68.12%
Student	41	4.36%	~6–10%	No	300	31.88%
Homemaker	16	1.70%	-	Mobility identity		
Parental leave	9	0.96%	-	Public transport user	368	39.11%
Retired	120	12.75%	~20–25%	Pedestrian	69	7.33%
				Cyclist	58	6.16%
				Car driver	218	23.17%
				Multimodal user	213	22.64%
				Others	15	1.59%

Monetary values are expressed in Hungarian Forints (HUF) converted to Euros with exchange rate of 400 HUF. Population values are approximate and based on official statistics from the Hungarian Central Statistical Office (KSH) and Eurostat, adjusted to match the closest comparable categories

Table 3 Exploratory factor analysis results

Item	Mean	PV perceived values	CP compatibility	TR trialability	OB observability	Uniqueness
PV1	3.11	0.920				0.142
PV2	3.30	0.872				0.180
PV3	3.37	0.647				0.202
TR2	3.80	0.375				0.528
CP1	3.18		0.911			0.159
CP2	3.18		0.771			0.204
TR1	4.00			0.745		0.266
TR3	3.80			0.738		0.266
OB2	4.30				0.409	0.565
OB3	3.60				0.676	0.383
OB1	3.63				0.622	0.428
SS loadings	-	2.66	1.95	1.67	1.49	-

Note: Maximum likelihood extraction with oblimin rotation was used. Loadings below 0.30 are suppressed for readability. The full rotated loading matrix is provided in Appendix B

values were then converted and reported in euros for readability. The most frequently reported household income range was 875–1,875 EUR (37.73%), while only 4.25% reported monthly incomes above 2,500 EUR.

Regarding mobility identity, understood here as respondents' self-reported identification with a transport-user group, the most common categories were public transport users (39.11%), car drivers (23.17%), and multimodal users (22.64%), while cyclists (6.16%) and pedestrians (7.33%) were less frequently selected. This pattern is consistent with Budapest's travel structure, where public transport and car use dominate, while cycling has a relatively small modal share. A majority of the respondents (68.12%) held a valid driver's license, indicating potential access to cars.

4.2 Exploratory factor analysis

Table 3 summarizes the factor structure after iterative testing, where the final solution yielded four interpretable factors corresponding to perceived values (PV), compatibility (CP), trialability (TR), and observability (OB), while the remaining DOI constructs were not retained due to insufficient representation in the factor solution. Overall, most items show their strongest loading on the expected latent dimension, indicating a coherent mapping between the retained constructs and the observed statements. TR2 loaded most strongly on PV, suggesting that having access to a cargo bike through one's social circle was more closely related to personal relevance and value alignment than to trialability alone. The SS loadings indicate that the PV factor has the largest share of variance among the retained dimensions, followed by CP, TR, and OB. Using these SS loadings relative to the 11 retained items, the four-factor solution accounts for approximately 70.6% of the total variance, which supports the adequacy of this reduced attitudinal measurement structure for subsequent segmentation. The KMO values of 0.90 and more, together with a highly significant

Table 4 Model fit metrics

Number of classes	Number of parameters	Log-likelihood	BIC (LL)	AIC (LL)	Entropy
2	43	-6147.11	12588.64	12380.22	0.91
3	78	-5496.37	11526.81	11148.75	0.87
4	113	-5193.22	11160.15	10612.44	0.89
5	148	-5036.46	11086.26	10368.91	0.83
6	183	-4822.23	10897.45	10010.46	0.85
7	218	-4704.80	10902.24	9845.61	0.88
8	253	-4583.96	10900.20	9673.92	0.88
9	288	-4595.27	11162.47	9766.55	0.88

Bartlett's test of sphericity, indicates that the dataset is well-suited for factor analysis, as the sampling adequacy is strong, and the variables show sufficiently high inter-correlations. To improve transparency, the full rotated loading matrix for all retained items is provided in Appendix B.

4.3 Model fit

After multiple iterations of EFA, selected factors combined with covariates formed the basis for assessing the model fit. Latent class models with 2 to 9 classes were estimated, and the results are summarized in Table 4. The 6-class model, which exhibited the lowest BIC together with reasonable parameter estimates and acceptable class proportions, was selected as the most appropriate solution.

4.4 Latent class cluster analysis

The results revealed differences in perceptions of SCB across the latent clusters (Table 5). The factors distinguished the groups estimated with the LCCA measurement model, where negative values indicate lower-than-average evaluations and positive values higher-than-average evaluations. Clusters 1 and 2 showed negative evaluations, Cluster 3 leaned toward

slightly negative tendencies, Clusters 4 and 5 held moderately positive views, while Cluster 6 displayed positive scores across all indicators. The reported coefficients follow the default Latent GOLD parameterization [28], where values are expressed relative to model constraints rather than a single reference category, which explains the symmetric patterns observed across some covariates.

In the structural model age, driver's license, and mobility identity were identified as meaningful predictors of cluster membership. Respondents aged 18–39 were more likely to appear in Clusters 4, 5, 6, while older age groups (55+) were concentrated in Clusters 1 and 2. Having a driver's license was weakly associated with Cluster 5, whereas non-drivers were more often found in Clusters 2 and 3. Mobility identity

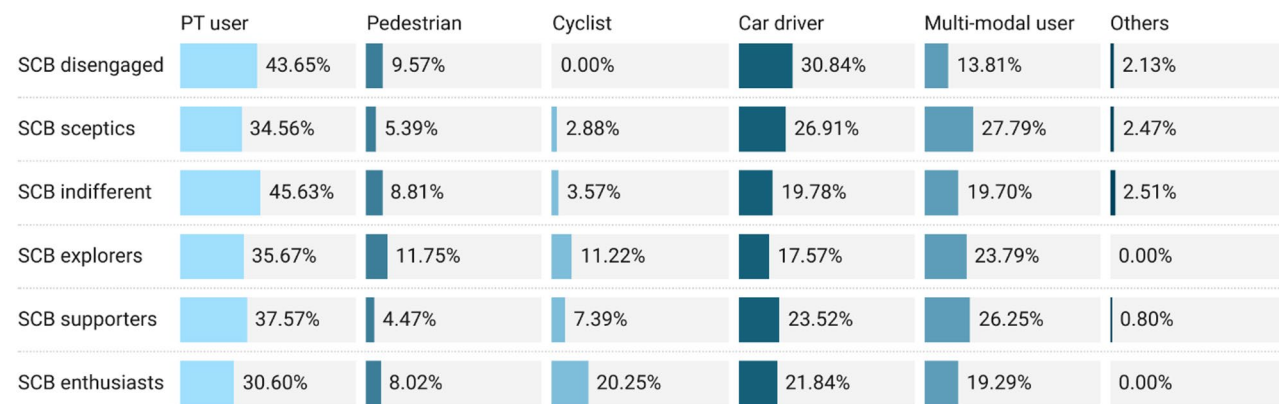
Table 5 Parameters of the LCCA model with 6 clusters

	Cluster1	Cluster2	Cluster3	Cluster4	Cluster5	Cluster6	Sig.
Measurement model							
PV	-2.3376	-1.6694	-0.3292	0.6146	1.1546	2.5670	**
CP	-2.2840	-1.6723	-0.1814	0.7160	0.8408	2.5809	**
TR	-2.8629	-0.8939	-0.2069	0.3532	1.2591	2.3514	**
OB	-1.6971	-0.9319	-0.2381	0.1742	0.7650	1.9279	**
Structural model							
Intercept	-0.0343	0.7307	1.3850	-1.3123	1.3751	-2.1442	**
Age							
18–24	-0.6473	-0.6033	0.1135	0.3979	0.5143	0.2249	
25–39	-0.6116	-0.4079	-0.0520	0.6928	0.3533	0.0254	
40–54	-0.2254	-0.0374	-0.1473	0.4800	0.0426	-0.1124	
55–64	0.4774	0.4074	0.1435	-0.1557	-0.5360	-0.3365	
> 64	1.0069	0.6412	-0.0576	-1.4149	-0.0576	0.1987	
Education							
Primary school	-0.4317	0.3091	0.0116	-0.1478	0.0245	0.2343	
High school	0.1571	-0.0095	0.0482	-0.0064	-0.1177	-0.0716	
Vocational education	-0.0888	-0.0330	0.0558	0.3165	0.1825	-0.4330	
University degree	0.3634	-0.2666	-0.1155	-0.1623	-0.0893	0.2703	
Employment status							
Employed	-0.8420	0.3502	-0.0917	0.4102	-0.4177	0.5910	
Unemployed	-0.8851	0.7813	-0.0427	0.6816	-0.0410	-0.4941	
Student	-0.7054	1.1001	0.3802	-0.8431	-0.3727	0.4409	
Homemaker	1.1190	0.9877	-1.1144	2.1187	-0.2779	-2.8331	
Parental or sick leave	2.1841	-3.9254	1.3529	-4.1290	1.4723	3.0450	
Retired	-0.8706	0.7060	-0.4843	1.7616	-0.3631	-0.7496	
Income							
Not reported	1.4071	0.8488	0.5551	0.9153	0.2564	-3.9826	
< 875€	-0.7134	-0.3108	-0.0861	0.0468	0.1652	0.8983	
875€<1875€	-0.4944	-0.3134	-0.1437	-0.1778	-0.0052	1.1345	
1875€<2500€	-0.3332	0.0284	-0.0768	-0.4551	-0.0836	0.9203	
≥ 2500€	0.1339	-0.2530	-0.2485	-0.3292	-0.3327	1.0295	
Number of children	-0.1472	0.2176	-0.0401	0.2775	0.1079	0.2913	
Household number	0.1379	0.0016	0.1226	-0.1355	-0.0543	-0.0723	
Driver's license							*
Yes	0.0555	-0.1548	-0.1619	0.0418	0.2571	-0.0378	
No	-0.0555	0.1548	0.1619	-0.0418	-0.2571	0.0378	
Mobility identity							**
PT user	0.7762	-0.5441	-0.4014	0.3563	-0.3447	0.1578	
Pedestrian	0.5885	-0.8332	-0.3209	0.7673	-0.7469	0.5453	
Cyclist	-4.5512	-0.2434	-0.1719	1.9063	0.6419	2.4184	
Car driver	0.8737	-0.0302	-0.5417	0.0324	-0.5466	0.2124	
Multimodal user	-0.0092	-0.2034	-0.5118	0.5568	-0.1534	0.3209	
Others	2.3220	1.8543	1.9477	-3.6190	1.1497	-3.6548	

** Significant at 95% confidence interval; * Significant at 90% confidence interval

Table 6 Cluster profiles

	SCB disengaged	SCB sceptics	SCB indifferent	SCB explorers	SCB supporters	SCB enthusiasts	Σ
Cluster size	28.19%	25.19%	19.08%	10.00%	8.92%	8.62%	100%
	265	237	179	94	84	81	941
Indicator	Mean						
PV	1.00	1.67	3.01	3.95	4.49	5.90	3.26
CP	1.00	1.61	3.10	4.00	4.12	5.85	3.18
TR	1.00	2.97	3.66	4.22	5.12	6.61	3.90
OB	2.19	2.95	3.65	4.07	4.65	5.81	3.84
Covariate	Share (%)						
Age							
18–24	4.31	5.90	12.98	5.45	11.04	8.82	9.24
25–39	20.20	20.18	33.74	41.05	42.12	43.10	33.37
40–54	27.64	33.92	33.66	39.56	33.74	35.25	33.79
55–64	23.39	17.33	12.49	8.30	6.19	7.50	12.12
> 64	24.45	22.66	7.17	5.65	6.89	5.33	11.48
Driver's lic.							
Yes	70.18	65.42	59.23	66.39	78.49	72.28	68.12
No	29.82	34.58	40.77	33.61	21.51	27.72	31.88

**Fig. 2** Distribution of mobility identities across attitudinal clusters

was the strongest differentiator across clusters. Cyclists more likely belong to Clusters 4, 5, and 6, while car drivers were predominantly found in Clusters 1. Pedestrians and multimodal users were divided, some associated with negative clusters and others with more positive ones.

4.5 Cluster profiles

The identified latent clusters reveal 6 attitudinal profiles toward SCB that differ not only in how respondents perceive PV, CP, TR, and OB, but in their socio-demographic composition and mobility identities. Table 6 summarizes the main characteristics of each cluster, showing statistically significant covariates, while Fig. 2 which illustrates the distribution of mobility identities across the clusters.

The disengaged group represents the largest share of the sample (28.19%). Their attitudes show strong resistance toward shared cargo bikes, as they do not perceive them as compatible with their lifestyle, valuable for their mobility, or easy to try. They express little interest in experimenting with

the service, which further reinforces their rejection. They are largely older respondents, with car drivers (30.84%) and public transport users (43.65%) making up the majority.

The sceptics also express limited perceived relevance of shared cargo bikes though less pronounced than among the disengaged, representing 25.19% of the sample. They also do not strongly identify with shared cargo bikes as a mobility option, showing limited alignment with the values and compatibility dimensions captured in the survey. While they recognize some potential for trialability and observability, they still see limited relevance to their daily travel needs. This cluster is dominated by public transport users (34.56%), car drivers (26.91%), and highest share of multimodal users (27.79%), with cyclists nearly absent (2.88%). They are typically middle-aged or older, reflecting a cautious or doubtful stance toward innovation.

The indifferent cluster falls in between, with neither strong rejection nor clear support, accounting for 19.08% of the sample. Their attitudes are neutral, showing

limited enthusiasm but also limited resistance. They tend to acknowledge shared cargo bikes as possible alternatives but lack strong motivation to adopt them. They are again overrepresented by older respondents and heavily composed of public transport users (45.63%). This group reflects a passive position, where adoption is unlikely unless clear and visible benefits are demonstrated. Their relatively high reliance on public transport also aligns with the highest “no driver’s license” share among clusters (40.77%), which may contribute to a more observational or conditional attitude rather than active adoption intent.

In contrast, the explorers express more positive attitudes, making up 10.00% of the sample. They see shared cargo bikes as potentially useful and somewhat easy to integrate, though they remain cautious about widespread use. Their perspective reflects curiosity and a willingness to experiment, rather than firm commitment. This group is more common among respondents younger than 55 and includes a diverse mix of mobility identities: public transport users (35.67%), car drivers (17.27%), pedestrians (11.75%), cyclists (11.22%), and multimodal users (23.79%).

The supporters display consistently favorable attitudes and represent 8.92% of the sample. They view shared cargo bikes as valuable and relatively easy to adopt, though not with the same intensity as the most positive cluster. Their attitudes suggest readiness to integrate shared cargo bikes if the service is accessible and convenient, but not necessarily a proactive search for adoption. Supporters are

more often younger and licensed drivers, with a balanced mobility mix: public transport users (37.57%), multimodal users (26.25%), and car drivers (23.52%). They are inclined to adopt if conditions align with their routines. This cluster also has the highest share of licensed respondents (78.49%), reinforcing that positive attitudes are not limited to non-drivers, but can include people with full car access who still see SCB as a viable option for specific trips.

Finally, the enthusiasts are the smallest group (8.62%) but most committed to adoption. They strongly perceive shared cargo bikes as compatible, valuable, easy to try, and visible in everyday life. Their attitudes reflect strong endorsement across all dimensions, marking them as innovation seekers. This cluster is younger (18–39), with cyclists (20.25%) and multimodal users (19.29%) making up a significant share alongside public transport users (30.60%) and car drivers (21.84%). Compared with the overall sample composition, cyclists are especially concentrated here, which aligns with the interpretation that this group is closest to early adopters and potential service ambassadors once an SCB system becomes available. This interpretation is additionally supported by shared micromobility research showing that adoption and use are closely linked to existing mobility habits and multimodal travel patterns [8, 25].

To support the interpretation of the latent clusters, Fig. 3 provides a concise overview of the six profiles along an adoption-readiness spectrum. The profiles summarize

Cluster	Size	Profile	Key characteristics
SCB disengaged	28.19%	Strongly resistant to SCB	Very low perceived value, compatibility and trialability; mostly older respondents; many public transport users and car drivers.
SCB sceptics	25.19%	Doubtful and unconvinced	Low perceived relevance; some recognition of trialability/observability, but little personal fit; more middle-aged/older; public transport, car, and multimodal users.
SCB indifferent	19.08%	Neutral/ movable middle	Neither clearly negative nor positive; weak motivation to adopt; many public transport users; highest share without driver’s license.
SCB explorers	10.00%	Curious and open to trying	Moderately positive attitudes; younger than 55; mixed mobility identities; willingness to experiment.
SCB supporters	8.92%	Positive and adoption-ready if service works well	Favorable attitudes; younger; many licensed drivers; balanced mobility mix; likely to adopt if service is accessible and convenient.
SCB enthusiasts	8.62%	Early adopters/ potential ambassadors	Highest scores across all dimensions; younger; cyclists and multimodal users more common; most likely to try and promote SCB.

Fig. 3 Readiness spectrum of potential shared cargo bike users

the main attitudinal and mobility-related characteristics of each latent cluster. Cluster labels are interpretative and are based on the retained DOI dimensions and covariate patterns.

5 Discussion

This study aimed to reveal heterogeneity among potential shared cargo bike users in Budapest by combining an adjusted Diffusion of Innovation measurement with Latent Class Cluster Analysis. The six-class solution demonstrates that pre-deployment adoption potential is structured in distinct attitudinal profiles rather than a single average willingness. While the analysis is based on data from Budapest, the identified attitudinal structure is not inherently context-specific. Similar patterns of heterogeneity in perceptions and adoption readiness have been observed in studies of shared mobility across different urban settings. Therefore, the profiles identified in this study are likely transferable to cities with comparable mobility systems and socio-economic conditions, although their relative size and distribution may vary depending on local context.

5.1 Policy implications

A key result is that class membership reflects a clear gradient across the retained attitudinal dimensions (perceived values, compatibility, trialability, observability). The most resistant clusters report very low compatibility and perceived values, while the most supportive clusters score high across all indicators. This gradient is consistent with the Exploratory Factor Analysis outcome, where in the sample the means suggest that trialability/observability are easier to endorse than “fit with my life” or “fits my values”, implying that many residents can imagine seeing cargo bikes and trying them, still do not see them as personally relevant. Thus, in an early-stage market can exist without translating into compatibility or perceived value, leaving a large share of potential users unconvinced.

The covariate results reinforce that openness to SCB is not reducible to demographics alone. Age differentiates clusters, with older respondents concentrated in the most negative profiles [7, 13], while younger respondents are more present in the exploratory and supportive profiles. At the same time, younger adults are not uniformly enthusiastic, and a sizeable portion is indifferent, indicating a movable middle rather than a simple young-old divide. This pattern suggests the presence of a broader group whose uptake may depend on reduced uncertainty and clearer evidence of practical value, rather than a group of immediate early adopters [24].

The strong role of mobility identity further underscores that SCB receptiveness is embedded in everyday user routines. The structural model identifies mobility identity

as the strongest differentiator across all clusters in the model, which aligns with broader evidence that multi-modality and mode-repertoires are heterogeneous and systematically linked to openness toward new mobility services [8]. Another notable implication of the results is that SCB interest is not limited to car-free residents. The supporters cluster contains the highest share of licensed respondents, showing that positive attitudes can exist even among people with driving access. This points to a plausible SCB role as an alternative for specific trip purposes rather than a niche option restricted to non-drivers. The finding is consistent with the broader insight that many city strategies for last-mile travel and goods movement depend on offering workable substitutes for selective car trips, not eliminating car use altogether [19]. This interpretation is also consistent with shared micro-mobility segmentation research, where user profiles are commonly differentiated by mobility routines, openness to new services, perceived barriers, and use motivations rather than by socio-demographic characteristics alone [9, 15].

The segmentation provides basis for targeted policy and service design, because each cluster reflects a different bottleneck. Rather than promoting SCB uniformly, the results suggest prioritizing interventions that address the dominant constraints of the largest group. Disengaged and sceptics, with a majority share, reduce perceived mismatch and perceived risk. For these groups, extremely low compatibility and perceived values indicate that messaging alone is unlikely to shift attitudes, unless accompanied by changes that make the service feel feasible and relevant. Built environment and safety conditions are especially important because perceived risk can outweigh functional benefits. Systematic evidence shows that cycling environment quality and traffic conditions are key determinants of willingness to use cargo bikes [6]. In Budapest, this implies that SCB deployment should be coupled with protected-route continuity and safe junction treatments, otherwise these groups will likely remain outside the reachable market, even if bikes are available.

Furthermore, indifferent respondents do not reject SCB outright, but they do not see a reason to adopt. This profile suggests that the most effective lever is making benefits observable in everyday contexts and translating the concept into credible use cases. A practical implication is to locate SCB facilities, where trip purposes are obvious (e.g., near retail clusters, family-oriented destinations, or multimodal transfer points), and to use short, structured demonstrations that connect SCB to routine errands. This aligns with the broader observation that SCB often remain niche unless they are embedded into mobility routines and service ecosystems [33]. These considerations with other policies to make driving less attractive (e.g. less car parking, more expensive parking)

can further nudge this indifferent group into adopting SCB. Also, evidence from DOI research suggests that hesitant attitudes can be reduced when uncertainty is lowered through trialability and observability, meaning that people can experiment with an innovation and see its benefits in practice [24]. In the shared eMobility context, Bokolo, [3] similarly emphasizes that understanding perceived adoption factors can support recommendations for increasing uptake of eMobility-sharing services.

In contrast, explorers and supporters already see meaningful perceived value and compatibility, their adoption is therefore sensitive to service performance, with availability, coverage, and ease of access at the moment of need being important factors for continued adoption. In scaling discussions, service integration and reducing user effort are repeatedly highlighted as prerequisites for moving beyond pilots [33]. In practical terms this means designing an SCB system with predictable availability, clear pricing, and low-effort rental workflows, so that willingness does not dissolve at the first failed booking attempt. Although being a small group, enthusiasts are highly positive across all dimensions and are most likely to try early and normalize the mode through visibility. This group can support uptake through peer-to-peer exposure and informal promotion once the service exists [24]. A concrete implication is to involve enthusiasts in early pilot recruitment and feedback loops to stabilize operations, while designing the service for broader groups.

While the policy implications discussed above already outline relevant intervention directions, it is clarified that these can be operationalized as targeted strategies aligned with each attitudinal segment. Specifically, disengaged and skeptical groups, interventions should focus on reducing perceived risk and increasing perceived compatibility, primarily through improvements in infrastructure, safety conditions, and low-threshold trial opportunities. Indifferent users can be addressed through increasing visibility and demonstrating concrete use cases in everyday contexts, for example through pilot programs located near key trip generators. The structural model identifies mobility identity as the strongest differentiator, where explorers and supporters can be targeted through service design measures that emphasize availability, accessibility, and ease of use, ensuring that initial interest translates into actual adoption. Finally, enthusiasts represent a suitable group for early engagement strategies, such as pilot participation, feedback mechanisms, and peer-to-peer promotion, helping to increase visibility and normalize the service.

These identified attitudinal profiles can also be interpreted as reflecting different levels of readiness for adoption across the population, with more positive segments, particularly explorers, supporters, and

enthusiasts, indicating the presence of a potential early market. This suggests that initial deployment strategies could focus on these groups to build early usage and visibility. At the same time, the distribution of less receptive segments indicates that broader uptake will depend on addressing perceived barriers and improving compatibility with everyday travel needs. Hence, this approach implies that effective targeting should rely less on demographic segmentation and more on aligning interventions with specific attitudinal barriers and readiness levels. However, these findings should be understood as indicative rather than as a direct estimate of expected demand.

Beyond these policy implications, the findings also have research relevance for the study of shared micromobility adoption. They show that potential SCB users should not be treated as a homogeneous group, since adoption readiness is structured around distinct attitudinal profiles. The combination of DOI-based measurement and LCCA therefore provides a useful approach for examining pre-deployment heterogeneity, not only for shared cargo bike systems, but in emerging mobility services in general and can support comparative studies in other urban contexts or after SCB systems become available.

5.2 Limitations and future work

Several limitations should be acknowledged. First, the study is based on self-reported attitudes in a pre-deployment context, which can introduce hypothetical bias and an attitude-behavior gap. Previous research shows that attitudes and behavior influence each other and may not align perfectly in cross-sectional measurements, particularly when respondents have limited direct experience with the option being evaluated [16]. A next step is to validate whether the identified profiles predict actual SCB uptake once the service becomes available.

Second, the use of quota-based online sampling aligned with age and gender limits the broader representativeness of the sample, which may affect the generalizability of the findings. Future research should address this by applying more comprehensive sampling strategies or post-stratification weighting approaches to better capture the full population structure.

Third, the measurement model required item reduction through the EFA, and two DOI constructs included in the survey (relative advantage and ease of use) were not retained in the final factor structure. This does not imply that these attributes are irrelevant, rather it reflects the difficulty of evaluating efficiency and operational usage without hands-on experience. Future surveys could address this by using more context-specific items (e.g., linking advantages to concrete trip types) and by testing the measurement model using confirmatory approaches with an independent sample.

Furthermore, while age, driver’s license, and mobility identity were significant covariates, most socio-demographic variables did not differentiate classes. This is analytically useful, indicating that attitudes are not simply demographic proxies, but it also suggests that additional predictors may matter, such as spatial context, cycling frequency, or proximity to SCB stations. Future research could therefore integrate objective built-environment measures and test whether profiles differ by neighborhood-level cycling conditions, which are linked to cargo bike adoption potential [6]. This study does not provide a quantitative demand estimation. Translating attitudinal segments into expected uptake would require alternative methodological approaches, such as discrete choice modelling or detailed revealed preference data. Extending the framework in this direction would enable a more direct assessment of demand for shared cargo bike services.

Finally, this analysis captures a static snapshot of heterogeneity. Because diffusion is dynamic, future work could use panel surveys or pilot data to examine transitions between groups over time (e.g., whether indifferent users become explorers after trial opportunities increase).

6 Conclusion

This study demonstrates a replicable framework for planning of emerging micromobility services, where DOI-grounded attitudinal measurement combined with LCCA produces actionable, interpretable profiles that can be used as a baseline for monitoring change once SCB is introduced. Hence, the study strengthens the empirical foundation for designing and evaluating SCB systems by showing who is ready, who is movable, and who is unlikely to respond without major shifts in perceived fit and value. Moreover, it is shown that potential SCB users in Budapest cannot be treated as a single market, as the LCCA identified six attitudinal profiles (disengaged, sceptics, indifferent, explorers, supporters, and enthusiasts) that differ in perceived value, compatibility, trialability, and observability.

As a key result, the disengaged and sceptics groups form a majority, while the clearly positive clusters of supporters and enthusiasts remain relatively small. Class membership is not explained by demographics alone, as mobility identity is the strongest differentiator, with cyclists and multimodal users concentrated in the more positive profiles, while car drivers are represented in the negative ones. Age reinforces this pattern by putting older respondents in the disengaged and sceptic profiles. Also, the structure of attitudes indicates that early-stage

uptake is primarily constrained by perceived fit and personal relevance, while trialability and observability are comparatively easier to endorse but insufficient on their own to move large shares of users into the adoption-ready groups.

These findings provide evidence that a large share of the population may remain resistant to SCB, meaning that uptake should be evaluated as a segmented diffusion process rather than a uniform response to service availability. In practical terms, the change should most likely start with the smaller receptive groups (explorers, supporters, and enthusiasts), while the indifferent cluster represents a potential expansion stage once uncertainty is reduced, and clear everyday use cases become visible.

7 Appendix

7.1 Appendix A. Survey questions

Question	Answers
What gender do you identify with?	• Man • Woman • Non-binary • Prefer to self-describe
How old are you?	• Enter number
Including yourself, how many people of each age group are living in your household?	• Up to 13 years of age • 14–17 years of age • 18+ years of age
What is the highest level of education that you have completed?	• No school completed • Primary education • Secondary education / high school • Vocational or technical training • Bachelor’s degree or equivalent • Graduate degree / postgraduate • Prefer not to answer
What is your current employment status?	• Employed full time • Employed part time • Self-employed • Student • Homemaker • Unemployed / Looking for work • Parental leave / sick leave • Retired / pensioner • Unable to work • Prefer not to answer
What is your household’s total monthly income, before taxes?	• Open question (enter number)
Do you have a valid driver’s license for passenger cars?	• Yes • No
I personally identify as a...	• Public transport user • Pedestrian • Cyclist • Car driver • Multi-modal person (i.e. I use and self-identify with a combination of modes) • Other

Question	Answers
How many of the following types of vehicles does your household own?	Enter number of vehicles... • Cars, Internal combustion engine • Cars, Hybrid vehicles • Cars, Battery Electric vehicles • Bicycles • E-bikes • Cargo bikes • Electric cargo bikes
In an average week, approximately how much total time do you spend traveling and how many trips do you take with the following modes of transport? Please consider travel from one place to another as one trip. The return will be counted as another trip.	Hours per week/Trips per week/ Not relevant... • Walk • Bike • E-bike • Cargo bike • Public transport • Shared bike • Shared e-scooter • Car sharing (as driver or passenger) • Taxi or Ride-hailing service • Personal car (as driver or passenger)
How much do you agree or disagree with the following? (Diffusion of Innovation) – items already listed in the manuscript - Compatibility - Perceived Values - Trialability - Relevant advantage - Observability - Ease of use	Scale from 1 to 7. • Completely disagree • Disagree • Rather disagree • Partly disagree, partly agree • Rather agree • Agree • Completely agree

7.2 Appendix B. Full rotated loading matrix for the final EFA solution

Item	Mean	PV per- ceived values	CP compatibility	TR trialability	OB ob- serv- abil- ity	Unique- ness
PV1	3.11	0.920	-0.016	0.009	0.020	0.142
PV2	3.30	0.872	-0.009	0.034	0.030	0.180
PV3	3.37	0.647	0.185	0.137	-0.017	0.202
TR2	3.80	0.375	0.180	-0.140	0.294	0.528
CP1	3.18	-0.027	0.911	0.009	0.037	0.159
CP2	3.18	0.086	0.771	0.071	0.008	0.204
TR1	4.00	0.152	0.002	0.745	-0.005	0.266
TR3	3.80	0.023	0.132	0.738	0.027	0.266
OB2	4.30	-0.086	-0.039	0.239	0.409	0.565
OB3	3.60	0.119	0.020	0.035	0.676	0.383
OB1	3.63	0.034	0.150	0.025	0.622	0.428
SS load- ings	-	2.66	1.95	1.67	1.49	-

Acknowledgements

The research was realized in the frame of the CargoNE-City project F-DUT-2022-0381, which is funded by Vinnova (Sweden); National Research, Development and Innovation Office, (Hungary/NKFIH); The German Aerospace Center (DLR); and Research Council of Norway (RCN) under the Driving Urban Transitions Partnership, which has been co-funded by

the European Union. Hungarian funding for CargoNE-City 2024-1.2.1-HE_PARTNERSÉG-2024-00010 project was implemented with the support of the Ministry for Innovation and Technology from the National Research, Development and Innovation Fund, based on a support document issued by the National Research, Development and Innovation Office. The authors are grateful for the support and preparation work of the whole research team. The linguistic revision of this paper is prepared by Eszter Tóth.

Author contributions

O.B. design of the work; data acquisition, analysis, and interpretation of data; software used in the work; wrote the main manuscript text. D.E.K. design of the work; reviewed the manuscript.

Funding

Open access funding provided by Budapest University of Technology and Economics.

Data availability

The datasets generated during and/or analyzed during the current study are available from the corresponding author on reasonable request.

Declaration

Competing interests

The authors declare no competing interests.

Received: 30 March 2026 / Accepted: 10 August 2026

Published online: 19 August 2026

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