IEEE Access
Multidisciplinary : Rapid Review : Open Access Journal

Received 4 June 2023, accepted 16 July 2023, date of publication 19 July 2023, date of current version 25 July 2023.

Digital Object Identifier 10.1109/ACCESS.2023.3297083

RESEARCH ARTICLE

The Preferences of Shared Micro-Mobility Users in Urban Areas

AHMED JABER[1], JAMIL HAMADNEH[2], AND BÁLINT CSONKA[1]

[1]Department of Transport Technology and Economics, Faculty of Transportation Engineering and Vehicle Engineering, Budapest University of Technology and Economics, 1111 Budapest, Hungary

[2]Department of Buildings, Roads, and Space Engineering, Faculty of Engineering and Technology, Palestine Technical University-Kadoorie, Tulkarm P304, Palestine

Corresponding author: Ahmed Jaber (ahjaber6@edu.bme.hu)

ABSTRACT This research focuses on the preferences of micro-mobility users in urban areas, specifically shared electric bikes (e-bikes), shared conventional bikes (bike), and shared electric scooters (e-scooters). It is found that previous scholars study traveler preferences of traditional transport modes while limited attention has been given to preferences of travelers toward micro-mobility considering electric scooters and bikes over conventional bikes. In order to address this gap, a discrete choice modeling approach is used to study the preferences of people through developing a transport choice model. A discrete choice experiment (DCE) is designed where choice sets that combine the shared micro transport modes where three associated attributes and four levels are included in the DCE for each alternative. A stated preference (SP) survey is designed and distributed in Budapest, Hungary. This research focuses on urban areas where travel time is relatively short. Multinomial Logit (MNL) model is applied where a transport choice model is developed. The effect of several factors on the preferences of people toward the three micro transport modes are evaluated. The developed transport choice model includes trip time, trip cost, walking distance, parking characteristics, and socio-demographic factors. The results indicate that travelers prefer using bikes more than e-bikes and e-scooters. Furthermore, it is found that e-scooter is the least favored by travelers. It is noteworthy that car drivers, individuals with access to or frequent usage of micro-mobility, graduate students, full-time workers, males, and young people are more willing to use shared electric micro-mobility services. The probability of choosing a transport mode based on the changes on parking type attribute is estimated in this research. The results show that travelers prefer free floating parking when they use shared electric micro-mobility services. This research underscores the significance of parking type (docks or dockless) and socio-demographic variables when it comes to micro-mobility modes in urban areas. It is evident that shared electric micro-mobility options require more effort and policy support to be effectively implemented, as shared conventional bikes appear more appealing to users. Overall, these findings contribute to the understanding of micro-mobility preferences and highlight areas for further exploration and potential policy interventions.

INDEX TERMS Discrete choice modeling, micro-mobility, transport mode choice, travel behavior, VOT.

I. INTRODUCTION

Recently, micro-mobility modes have become increasingly popular because they provide a fast and flexible last-mile transport service and help reduce traffic and pollution [1], [2], [3]. In addition, they form interesting modes for exercise and recreation [4], provide mobility services to residents and visitors [5], as well as enable door-to-door travel [6]. Therefore, several municipalities expressed their commitment to micro-mobility modes worldwide. E.g., the Hungarian authorities allocated a budget of HUF 1 billion to acquire over 7,000 e-bicycles [7]. Micro-mobility utilization in Budapest, Hungary, increased from 7.5% to 12% between 2016 and 2022 [8]. Currently, 2491 bikes are available at one of the 316 stations, and approximately 2000 e-scooters are shared in a free-floating system in the city [9], [10], [11].

The associate editor coordinating the review of this manuscript and approving it for publication was Zhe Xiao.

However, a high modal share of shared mobility services is not expected because they are mainly complementary to conventional public transport and private soft mobility modes. Still, with other sustainable transportation modes, they form a competitive mobility palette with private car ownership, reducing the number of cars in the service area.

Accordingly, it is essential to understand user choices because it helps to provide high-quality services that attract more users. Due to their novelty, new operational challenges arise, such as dock-based or dockless service to meet the demand, service area determination, tariff system, maintenance, regulations, and policies [12], [13]. Namely, the integration of micro-mobility services into the transportation system necessitates the understanding of user behavior.

Few studies have focused on the preferences of shared electric micro-mobility users. Stated preferences pertain to opinions expressed before a project is initiated, whereas stated preferences refer to opinions expressed by someone who has used the project while it is in operation. This study uses a discrete choice modeling survey to determine how the relative importance of several independent attributes impacts the use of specific micro-mobility modes. The model's novelty is that a broader range of factors, including time, cost, and various socio-demographic characteristics, were considered. Survey participants select a transport mode among one of the following: Shared Electric-Bike (E-Bike), Shared Conventional Bike, and Shared Electric Scooter (E-Scooter) based on trip time, trip cost, access time to and from a soft transport mode, and parking type after finishing a trip. We distinguished ''Parking lot'' and ''Free floating'' parking types because the parking lot is better known than station based, and they catch better the service characteristics instead of docked and dockless. E.g., a station-based bike-sharing service is used in Budapest, Hungary, without docks. These soft micro-mobility modes have been chosen, as the users don't require a driver's license to use them, these modes are somehow limited to use in urban areas, and they are all accessed via mobile applications. Decisions are analyzed in a metropolitan area, where distances are small, and trip purposes are routinely the same daily.

The latest methodologies employed in micro-mobility research include the logit models, negative-binomial and Poisson models, geographically weighted regressions, the random forest approach, etc. Recent studies have used these methods to investigate various aspects of micro-mobility preferences and travel mode choice. We will provide a concise summary of these methodologies to enhance the comprehensiveness of our research in the literature review section. In our research, we chose the mixed logit model for its flexibility and ability to handle diverse data and complex decision-making processes. While Although Machine Learning and ANN methods have shown promise, we did not directly compare them in this study due to the specific capabilities and requirements of the mixed logit model, and could be a future work.

However, despite their potential, achieving a high modal share of shared mobility services is challenging due to their complementary nature to conventional public transport and private soft mobility modes [14].

The rest of the paper is structured as follows: in the literature review, the background and some relevant studies are summarized. Section III discusses the methodology, which includes the survey and analysis. The results are shown in the following section, and the findings are discussed in Section V. Finally, Section VI provides the conclusion.

II. LITERATURE REVIEW

Because of the mixed logit model's flexibility and ability to approximate any random utility specification, this model has become one of the most popular techniques for discrete choice modeling [15]. Reck et al. [16] used a multinomial logit model to reveal how distance, location, vehicle density, time of day, and battery capacity influence commuters using electric bikes and scooters. Demographic characteristics were not considered. Close to our research, Reck et al. [17] focused on the enviornmental impacts on shared micro-mobility using a mixed logit model, they excluded travel time, walking time and travel cost. User willingness to use shared micro-mobility was measured for 200 meters or shorter distances to the nearest free vehicle. It was found that the weather heavily influences micro-mobility choices. Based on a logistic regression model, Rayaprolu and Venigalla [18] indicated that different forms of micro-mobility are used differently due to motivation and trip distance. Safety is considered one of the main drawbacks of the micro-mobility systems, which needs deeper evaluation rather than stated preference techniques, while cost is one of the most significant positive factors but requires time parameters for better assessment.Continuing their work, Reck and Axhausen [19] created a different model using the multinomial probit model to represent the demographic data. Users of Zurich's shared micro-mobility services are typically young, male, university-educated professionals who are gainfully employed and live in affluent single-person households without children and/or cars.

Using an ordinal logit model, Campisi et al. [20] analyzed the impacts of population, car ownership, infrastructure service, traveler safety perception, comfort, and environment on shared micro-mobility. Findings showed that the increase in car ownership and age decreases the willingness to use shared micro-mobility. While most previous studies depended on one way of analysis, Zhao et al. [21] analyzed the results of a machine learning and a logit model comparison to determine the preferred transportation mode among cars, bikes, public transport, and walking. The advantages and disadvantages of driving, strolling, pedaling, and bus use were weighed and balanced. Logit models outperformed machine learning and tree-based approaches, according to the findings. Furthermore, another study involved micro-mobility options in mode choice modeling [22]. Researchers used multinomial logit models to learn more about how people choose their mode to reach several facilities. There were substantial effects from individual, trip, and land use factors. The likelihood of using micro-mobility was highest for travels to universities/colleges and sporting events. Recently, Kutela et al. [23] have focused on people's preferences on micro-mobility using Bayesian Networks. Shared electric micro-mobility modes and cost, walking time, accessibility, frequency, motivation, and occupation were not considered. Kutela et al. [24] concentrated on autonomous vehicle preferences with respect to bike-sharing and electric scooters. Their main scope is to study the emergence of AVs in the transportation system. Our research focuses on shared electric micro-mobility emerging in the transportation system. Shared electric bikes and shared electric scooters were not considered.

Beyond the logit models, several methodologies have been applied to discuss the micro-mobility preferences and the factors affecting travel mode choice. The negative-binomial model was conducted to reveal shared micro-mobility preferences in different weather [25]. Results showed that weather was less disutility for scooter-sharing users than for bike-sharing users, regardless of membership type. Based on a similar approach but extended within GIS spatial analysis, Bai and Jiao [26] emphasized that green space and commercial location positively correlate to electric scooters. Additionally, Caspi et al. [27] found that students are the primary users of shared electric scooters using a geographically weighted regressions model. Furthermore, Jaber et al. [8] highlighted the impact of public transportation line distribution on bike-sharing trips based on ordinary least square and geographically weighted regressions. Furthermore, Hatami et al. [28] applied the random forest approach to model the mode choice among active mobility and public transportation. In their research, the authors highlighted the importance of studying sustainable transportation means such as electric bikes in future studies.

With this focus through our research on time parameters, we provide a review of literature that discusses this matter and other factors. Nowadays, everyone tries to get where they are going as quickly as possible since travel time has a low value [29], [30]. Guevara [31] presents three parts of travel time: waiting time, walking time, and trip time. Guevara found that waiting time is the least favorable for travelers. Travel time is a loss that should be minimized [32], [33]. Belenky [29] reveals that consumers will pay more to avoid potentially unpleasant aspects of travel, such as waiting and crowding. Among others, the value of time spent in transit is based on motivation, passenger demographics, travel conditions, geographical location, and departure and arrival times [34], [35], [36]. Besides time factors, many academics have examined the qualitative and quantitative factors influencing travelers' mode selection. Litman [37] demonstrates that infrastructure developments are more costly than value of travel time (VOT) reduction based on qualitative measures (e.g., the construction of a bridge). The study concludes that people will switch modes of transportation if certain factors are altered, such as increased convenience or comfort, and that travelers are more loyal to a transportation service if it provides a suitable environment. Perk et al. [38] illustrate that people's travel habits vary not only from one another but also through time and in response to environmental influences, such as weather conditions, congestion, etc. Cirillo and Axhausen [39] argue that high service quality increases the service area and the maximal travel distance where the service is competitive with other transportation modes. For example, Kolarova et al. [40] reveal that users with higher incomes are more willing to pay to decrease the utility of travel time. The cost is seen as the main factor affecting shared electric micro-mobility systems. Compared to a more innovative system, the conventional micro-mobility system's charging costs are much higher due to the high repositioning rates [41]. According to Elhenawy et al. [12], the suppliers will pay for everything, relieving the management team of any responsibility. Shared policies have costs, but customer incentive payments to suppliers will help cover those costs. Other motivations could be the ease of access [42], [43]. This is highlighted as a future intention to use shared electric micro-mobility that positively affects individuals' decisions.

The literature review indicates that the mixed logit model is appropriate for our study because it considers both the panel structure of our data and the fact that individuals have varying preferences when selecting their preferred transportation mode [15]. The discussed studies focus on modeling the conventional micro-mobility options (bikes and scooters), as well as investigating the differences between shared electric micro modes in aspects of availability and cost. However, the shared electric micro-mobility options in aspects of time, cost, and parking type were limitedly considered in the literature. The paper's main contributions are predicting and modeling the travel behavior in the presence of three soft transport modes (conventional bike-sharing, electric bike-sharing, and electric scooter-sharing) and highlighting people's acceptability to the electric soft modes over other conventional operating bikes.

As shown in Table 1, several recent papers studied the micro-mobility mode choice in several aspects. Accordingly, most of them have not focused on the three micro-mobility modes of conventional bike-sharing, electric bike-sharing, and electric scooter-sharing, or several factors have been neglected. Thus, the uniqueness of this study stands as it deals with the preferences of shared electric micro-mobility with respect to each other and how these modes affect the usage among them. In addition, previous studies that have focused on the preferences of these modes have not included the time parameters or the cost.

The main aspects that have been considered are travel time, cost, walking distance, parking type, socio-demographic characteristics, and micro-mobility ownership, which all will be revealed using discrete choice modeling. To summarize the research questions:

TABLE 1. Summary of recent literature on different micro-mobility services factors affecting the mode choice.

Research Article	BS	SEB	SES	Factors Studied	Factors not studied
Reck et al. [16]	Yes	Yes	Yes	distance, location, price, vehicle density, time of day, and battery capacity	Travel time, walking time, and demographic characteristics
Reck et al. [19]	No	Yes	Yes	Distance, weather, time of day, demographic characteristics, and public transport connectivity	Travel time, walking time, income, frequency, accessibility to personal micro-mobility modes, and cost.
Rayaprolu and Venigalla [18]	Yes	Yes	No	Demographic characteristics	Travel time, walking time, cost, accessibility to personal micro-mobility modes, frequency, occupation, and education.
Reck and Axhausen [19]	No	Yes	Yes	Demographic characteristics, priorities, income, and public transport connectivity	Travel time, walking time, accessibility to personal micro-mobility modes, frequency, and cost.
Campisi et al. [20]	Yes	No	No	Demographic characteristics, and accessibility to personal micro-mobility modes	All other factors
Zhao et al. [21]	No	No	No	Demographic characteristics, level of service, and current mode choice	All other factors
Azimi et al. [22]	Yes	No	No	Location, time of day, accessibility, and demographic characteristics	All other factors
Kutela et al. [23]	Yes	No	No	demographic characteristics, and income	Cost, walking time, accessibility, frequency, motivation, and occupation
Kutela et al. [24]	Yes	No	No	demographic characteristics, and in respect to AV	All other factors
Younes et al. [25]	Yes	No	No	Time of day, and weather	Demographic characteristics, travel time, walking time, cost, and parking type
Bai and Jiao [26]	No	No	Yes	demographic characteristics, distance, and land use	All other factors
Caspi et al. [27]	No	No	Yes	Time of day, public transportation connectivity, and land use	Demographic characteristics, travel time, walking time, cost, and parking type
Jaber et al. [8]	Yes	No	No	Proximity to public transport, and priority levels	Demographic characteristics, travel time, walking time, cost, and parking type
Zhu et al. [41]	Yes	No	No	Location, time of day, and land use	Demographic characteristics, travel time, walking time, cost, and parking type
Elhenawy et al. [12]	No	No	Yes	Trip duration, trip distance, time of day, and location	Demographic characteristics, travel time, walking time, cost, and parking type
Soltani et al. [4]	Yes	No	No	Demographic Characteristics, and land use	All other factors

BS: Bike-sharing
SEB: Shared electric bikes
SES: Shared electric scooters

1) What are people's preferences towards shared electric micro-mobility in aspects of time and cost?

2) How do the shared electric micro-mobility impact each other?

III. METHODOLOGY

The factors influencing traveler mode choice include the attributes of the transportation mode and the traveler's preferences towards the choice. A SP (stated preference) survey is used as a first step in building discrete choice modeling. In general, discrete choice modeling is used to learn how users evaluate the aspects of a service or product by having them select their preferred option from a set of hypothetical options, consistent with the random utility theory [44], [45]. In this paper, the SP is made up of two distinct elements: the first is the socio-economic and trip information (See Appendix). The data collected consists of demographics such as income, age, gender, education, occupation, mode of transportation, destination, and trip purpose. The second is the discrete choice experiments (DCEs) via which travelers select their preferred transportation mode. The DCE provides a value for a set of alternatives, and can reveal how much people are willing to pay for specific attributes of those alternatives [46]. In this survey, the attributes affecting choosing an e-scooter, e-bike, and conventional bike are trip time, trip cost, walking to and from a transport mode, and parking type after a trip. The attributes were determined based on the literature, the authors' observations, and their experiences.

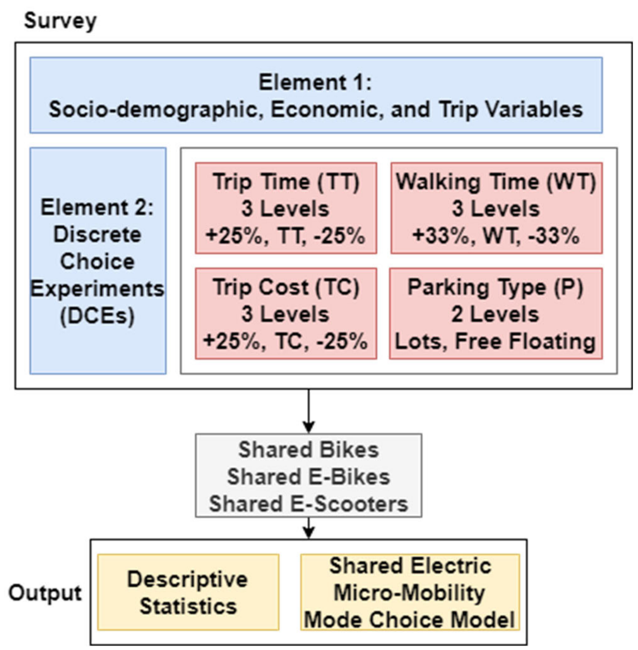


FIGURE 1. The approach of the methodology.

In addition, survey answeres about the characteristics of each mode of transportation are investigated using an SP technique to extract responses that detect priorities, choices and the relative significance of individual elements. The paper's methodology is presented in Figure 1.

The survey includes questions on socio-demographic, economic, and travel information, and discrete mode choice questions

A. DCE SPECIFICATIONS

The discrete choice experiments include shared conventional bikes, shared e-bikes, and shared e-scooters as alternate modes of transportation. In Table 2, we see the various combinations of time, cost, and parking-type characteristics that can be used to estimate the cost of using traditional transport options using actual data [47]. In the survey, respondents are presented with set of decision situations, consisting of three options and asked to choose based on their own preferences and the survey's instructions. Two attribute levels for parking type and three attribute levels for time and cost were introduced. We have chosen the levels to show the range of situations that respondents might face to improve the reliability of answers help generating comparable decision situations. Table 2 summarizes the parking types, relative walking time, trip time, and cost.

Due to the enormous number of possible outcomes from a full factorial design, a fractional factorial design is used to develop the discrete choice experiment design with six discrete choices [48], [49]. The level values are summarized for each option and equal in a set. RStudio is used to generate all of the combinations for the fractional factorial design. Each row of the orthogonal main-effect array stands for a unique set of permutations. The DCEs are generated using the "Lma.design" function in the "support.CEs" package of StataBE 17. Table 3 displays a sample discrete choice in the survey.

TABLE 2. Attributes and their levels in the choice sets.

Levels	Attributes			
	Parking type	Walking Time (WT) (minutes)	Trip Time (TT) (minutes)	Trip Cost (TC) (HUF)
L 1	Parking lots	133%	125%	125%
L 2	Free floating	100%	100%	100%
L 3	-	67%	75%	75%

TABLE 3. A sample combination.

			
Transport mode	**Shared E-Bike**	**Shared Bike**	**Shared E-Scooter**
Trip Time (minute)	**20**	**15**	**15**
Trip Cost (HUF)	**400**	**750**	**600**
Walking time (minute)	**8**	**6**	**4**
Parking Type	**Parking lots**	**Free floating**	**Parking lots**

1 EUR = 400 HUF

B. MIXED LOGIT (ML) MODEL

According to the random utility theory, all passengers rational decision-makers seeking to maximize utility [50]. Two components form the utility function; the deterministic (V) and the stochastic (ε). The deterministic quantity shows travelers' average perceived utility. The stochastic component determines the data-fitting model and model accuracy [50]. The perceived utility (U) of option j for individual i in mode choice situation c is given in Equation 1.

$$U_{ijc} = V_{ijc} + \eta_{ijc} + \varepsilon_{ijc} \tag{1}$$

where V_{ijc} is the deterministic component that represents a part of the utility of the individual i to choose alternative j. ε_{ijc} is a random error, independent and identically distributed (IID) extreme value that applies to all options, individuals, and choice scenarios. The random term η_{ijc} has zero mean, a heteroskedastic, and correlated over the alternatives. Further details on the method can be found in [51], [52], [53], and [54]. Noting that we have extracted equation 1 from these mentioned references, while the utility function in equation 2 is the application of our model using the referenced equation.

$$\begin{aligned} U_{ijc} = {} & \beta_{o(i)} + \beta_{TC(i)}{}^{*}TC \\ & + \beta_{TT(i)}{}^{*}TT + \beta^{*}_{WT(i)}WT + \beta_{PT(i)}{}^{*}PT\ (D) \\ & + \beta_{Tranportmode(i)}{}^{*}The\ regular\ tranport\ mode\ (D)\ {}^{*}D_j \\ & + \beta^{*}_{AccesstotoMicroMobility(i)^{*}} \\ & \quad Accessability\ to\ Transport\ Mode\ (D)\ {}^{*}D_j \\ & + \beta_{Freq.of\ \ Use(i)}{}^{*}Frequency\ of\ \ Use\ (D)\ {}^{*}D_j \end{aligned}$$

$$
\begin{aligned}
&+ \beta_{education(i)}{}^{*}education\ (D)\,{}^{*}D_j \\
&+ \beta_{Gender(i)}{}^{*}Gender\ (D)\,{}^{*}D_j \\
&+ \beta_{Destination(i)}{}^{*}Destination\ (D)\,{}^{*}D_j \\
&+ \beta_{Age(i)}{}^{*}Age\ (D)\,{}^{*}D_j \\
&+ \beta_{income(i)}{}^{*}income\ (D)\,{}^{*}D_j \\
&+ \beta_{Job(i)}{}^{*}Job\ (D)\,{}^{*}D_j + (\varepsilon + \eta)_{ijc} \qquad (2)
\end{aligned}
$$

The travel cost, trip time, walking time, and parking type are represented as TC, TT, WC, and PT, respectively. β components are observed variable parameters to be estimated from data, while $\varepsilon + \eta$ indicates an indeterministic error. The alternate dummy (D) is either 0 or 1 based on the existence of a variable, while the dummy (Dj) is a term showing that there is a referenced alternative. The VOT is given in Equation (3), extracted from Sun et al. research [55].

$$VOT = \frac{\beta_{tt}}{\beta_{tc}} \qquad (3)$$

C. THE SAMPLE DESCRIPTION

The survey was shared via email and social media to reach a wider audience with an emphasis on college students. In general, well-educated young people are the early adopters of shared electric micro-mobility services because they are environmentally conscious and open to new technologies [56]. Furthermore, micro-mobility completes conventional public transport, and older generations are more likely to have a higher income and prefer private transportation modes. Although the sample does not represent the population well, the findings help electric micro-mobility service providers to better understand their primary target group, especially in the early phase. Usually, the sample random size method is applied to evaluate the sample size [57]. Based on that, the minimum sample size is 385 responses. In discrete choice modeling, the Bekker-Grob et al. formula is also widely applied [58]. Based on that, 125 responses would be sufficient for the analysis. Our sample size of respondents is valid because 389 respondents answered the survey between March and April 2022.

Table 4 displays the socio-demographic and travel characteristics of the respondents. Males and females are approximately equally represented in the sample, representing the population well. The survey largely covers the preferences of young people, namely those aged between 18 and 24 (43.7%). Most participants (89.5%) had undergraduate/graduate degrees. About 32.1 % of the participants possess full-time jobs, which is close to the population statistics of 31.7% [59], 7.5 % hold part-time jobs, 44.5 % are students, 6.2% are self-employed, 5.7% are retired, and 1.3% are unemployed (Table 4), which is also close to the population statistics of 2.04% [60]. The average net income in our study is 252,760 HUF, close to the Hungarian average net income of 260,144 HUF.([61]. As 44.5% are students, and 29.6% have low incomes, this would mean that there are students with scholarships or part-time jobs. Important research ethics, including respect for participants' privacy and anonymity, have been considered in this survey.

TABLE 4. Descriptive statistics on the sociodemographic variables.

Category		%
Educational Level	Graduate studies	41.7
	Undergraduate studies	47.8
	High school	10.0
	Others	0.5
Employment	Student	44.5
	Full-time worker	32.1
	Part-time worker	7.5
	Self-employed	6.2
	Retired	5.7
	Unemployed	1.3
	Others	2.7
Age	18-24	43.7
	25-54	52.7
	55-64	3.1
	+65	0.5
Accessibility	Only Bike	26.7
	Only Scooter	2.8
	Both	11.1
	None	59.4
Income	Low	29.6
	Average	27.5
	High	24.4
	No answer	18.5
Gender	Male	56.8
	Female	43.2

This study's limitations include its emphasis on short trips in urban areas. In addition, the sampling does not represent the entire population. It should be noted that a wide variety of users, especially college students, are asked to fill out the survey. The study's findings hinge on the existing transportation network in Budapest; hence, the availability of infrastructure and the travel habits of locals may impact the study's findings.

Table 5 indicates participants' shared micro-mobility mode, purpose, and frequency. Most responders (43.4%) use public transportation, while 28.3% drive cars and 14.4% use non-motorized modes. Shared micro-mobility is most popular for leisure (50.9%), followed by work (20.3%) and school (20.3%). It is observed that 11.6% of respondents use shared micro-mobility services several times a month. Furthermore, 5.1% of respondents who do not have access to personal micro-mobility modes use shared micro-mobility services. It supports our fundamental aim that there is a need for user preference research to reveal the barriers and increase market penetration. Over 72.5% of participants do not use shared

TABLE 5. Statistics on participants' trip purposes, modes of transportation, and frequency.

Category		%
Main daily transport mode	Public Transportation	43.7
	Shared bike-scooter	1.0
	Car as passenger	10.3
	Car as driver	28.3
	Walking	8.0
	Taxi	3.1
	Personal bike or scooter	5.4
	Other	0.2
Main trip purpose if using shared micro-mobility	Work	20.3
	Educational	20.3
	Leisure or others	50.9
	Shopping	3.9
	Home	4.6
Frequency of using shared micro-mobility	Daily	1.5
	Weekly	10.1
	Monthly	15.9
	Never	72.5

micro-mobility, while 40.6% (Table 5) of the respondents have access to personal micro-mobility. That means some people might not use the shared micro-mobility but use their personal micro-mobility modes, and vice-versa.

IV. RESULTS AND DISCUSSION

A. MODEL DEVELOPMENT

Many models with different error distributions, such as random, log normal, uniform, triangular, and Gaussian, are evaluated before selecting the best-fit model. The Bayesian Information Criterion (BIC) model with the lowest BIC is chosen. Table 6 summarizes the results of the mixed multinomial logistic regression parameter, which is the best-fit model.

The model performance results for the model are presented in Table 7. Akaike's information criterion (AIC) is a fined method based on in-sample fit to estimate the likelihood of a model for predicting future values [62]. Bayesian information criterion (BIC) estimates the trade-off between model fit and complexity of the model [63]. A lower AIC or BIC value is preferred. It is shown that the model has a BIC of 4836.15, a log simulated likelihood of -2179.018, and statistical significance with 7002 observations. Compared to other models in the literature, these values are acceptable relatively as they are lower than Azimi et al. [22], and Kutela et al. [24], with an AIC of 6528.7 and 13630.6, respectively.

B. MODEL ESTIMATES

The results show that increased trip duration, walking time, and travel cost significantly impact travelers' decisions. However, parking type has either a beneficial or negative impact on mode choice. There is a 0.067 decrease in mode choice for every unit increase in trip time and a 0.084 point decrease in mode choice for every unit increase in walking time. In addition, a 0.002 decrease in mode selection is related to a one-unit rise in the travel cost variable. The model was created using the HUF unit's trip cost and the minute unit's trip time as inputs. Equation 3 estimates travelers' willingness to pay for travel time saving from marginal effects. According to the model, the travelers' VOT is 2010 HUF per hour (i.e., 5 Euro per hour). Compared to other studies, the VOT in our research is lower than [64] with a VOT of 18.5 Euro/hour and [65] with a VOT of 16.02 Euro/hour, and close to the findings of [66] with a VOT of 3.1 Euro/hour. This could be explained by the fact that the latter study and ours have used income and age categories to control individuals' socio-economic characteristics, which can reduce the coefficients of time if it is correlated with age and income. All variables are 99% significant. The likelihood of choosing a transport mode with a parking lot is 0.608 times lower than the probability of free-floating parking (i.e., the relative risk ratio).

Furthermore, the model examines other variables such as transportation mode, trip purpose, frequency, education, gender, age, income, job, and accessibility to micro-mobility to assess their effects on travelers' utility. The utility and the probability ratio are represented by the coefficient value (β) and Exp (β), respectively. Table 5 shows how the significance of these variables.

V. DISCUSSION

A. VARIABLES INTERPRETATION

1) FOR THE REGULAR TRANSPORT MODE VARIABLE

E-bikes exhibit significant outcomes with a 99% confidence level. The relative risk ratio for the car as a passenger is 0.566 (i.e., the chance of using e-bikes for car passengers is lower than for drivers). The related risk ratios for walking, public transport, taxi, and personal micro-mobility are 0.227, 0.533, 0.394, and 0.495, respectively. It means passengers who use these options are less likely to use e-bikes than car drivers. Car drivers prefer e-bikes over other types of transportation. According to Pase et al. [14], most bike-sharing users reported reduced car usage over public transit utilization. Both studies highlight the shifting towards sustainabile micro-mobility from car usage.

In the case of e-scooters, all modes of transportation except public transportation exhibit significant outcomes at a different confidence level: walking and micro-mobility at 99%, taxi at 95%, and car as a passenger at 90%. Car as passenger, taxi, walking, and micro-mobility have relative risk ratios of 0.76, 0.557, 0.397, and 0.301. It indicates these travelers are less likely to utilize e-scooters than car drivers.

2) FOR ACCESSIBILITY AND FREQUENCY OF USING PERSONAL MICRO-MOBILITY

Regarding accessibility to private micro-mobility mode, with a relative risk ratio of 1.273, travelers with access to personal

TABLE 6. Results of the model regression.

Alternative	Attribute	Coefficient (B)	Std. err.	z	P>z	Exp(B)
	Trip Time	-0.067	0.007	-10.13	0.000	0.935
	Travel Cost	-0.002	0.000	-12.17	0.000	0.998
	Walking Time	-0.084	0.017	-5.08	0.000	0.919
	Parking Type (lots)	-0.498	0.057	-8.68	0.000	0.608
E-Bike	Transport Mode					
	Car as passenger	-0.570	0.196	-2.90	0.004	0.566
	Public Transport	-0.630	0.157	-4.01	0.000	0.533
	Taxi	-0.931	0.311	-3.00	0.003	0.394
	Walking	-1.483	0.236	-6.28	0.000	0.227
	Micro-mobility	-0.704	0.257	-2.73	0.006	0.495
	Other	-1.227	1.257	-0.98	0.329	0.293
	Accessibility to micro-mobility (YES)	0.241	0.131	1.85	0.065	1.273
	Frequency					
	Daily	1.370	0.524	2.62	0.009	3.937
	Never	0.697	0.204	3.41	0.001	2.007
	Monthly	0.779	0.219	3.56	0.000	2.179
	Education					
	High school	-0.642	0.191	-3.36	0.001	0.526
	Other	-16.749	1305.394	-0.01	0.990	0.000
	Undergraduate studies	-0.317	0.120	-2.64	0.008	0.728
	Gender (Male)	0.203	0.113	1.80	0.072	1.225
	Destination (Work, shopping, and education (WSE))	0.419	0.113	3.72	0.000	1.520
	Age (>=44)	-0.243	0.201	-2.21	0.027	0.784
	Income					
	I prefer not to answer	0.076	0.168	0.45	0.652	1.079
	Low	0.408	0.173	2.37	0.018	1.505
	Medium	-0.102	0.163	-0.63	0.531	0.903
	Occupation					
	Part-time worker	0.190	0.216	0.88	0.079	1.209
	Self-employed	-1.061	0.245	-4.33	0.000	0.346
	Unemployed	0.073	0.441	0.16	0.869	1.076
	Student	-0.435	0.164	-2.65	0.008	0.647
	Retired	-0.112	0.251	-0.45	0.655	0.894
	Constant	-0.286	0.273	-1.05	0.295	0.751
E-Scooter	Transport Mode					
	Car as passenger	-0.267	0.241	-1.11	0.066	0.766
	Public Transport	-0.094	0.188	-0.50	0.618	0.910
	Taxi	-0.585	0.389	-1.50	0.033	0.557
	Walking	-0.923	0.270	-3.42	0.001	0.397
	Micro-mobility	-1.201	0.342	-3.51	0.000	0.301
	Other	1.136	0.990	1.15	0.251	3.114
	Accessibility to micro-mobility (YES)	0.178	0.153	1.17	0.244	1.195
	Frequency					
	Daily	2.052	0.504	4.08	0.000	7.787
	Never	-0.097	0.219	-0.44	0.658	0.908
	Monthly	0.254	0.229	1.11	0.069	1.289
	Education					
	High school	-0.438	0.218	-2.01	0.045	0.645
	Other	0.572	0.620	0.92	0.356	1.771
	Undergraduate studies	-0.188	0.139	-1.35	0.078	0.829
	Gender (Male)	0.162	0.130	1.240	0.214	1.176
	Destination (Work, shopping, and education (WSE))	0.281	0.132	2.14	0.033	1.325
	Age (>=44)	-0.969	0.299	-3.24	0.001	0.379
	Income					
	I prefer not to answer	0.082	0.204	0.40	0.686	1.086
	Low	0.556	0.200	2.78	0.005	1.743
	Medium	0.368	0.188	1.96	0.050	1.445
	Occupation					
	Part-time worker	0.058	0.255	0.23	0.821	1.060

TABLE 6. ***(Continued.)*** **Results of the model regression.**

	Self-employed	-0.255	0.266	-0.96	0.138	0.775
	Unemployed	-0.836	0.687	-1.22	0.084	0.433
	Student	-0.261	0.190	-1.37	0.070	0.770
	Retired	-1.326	0.373	-3.55	0.000	0.266
	Constant	-0.751	0.311	-2.42	0.016	0.472

TABLE 7. **The statistics of the model.**

The number of observations	7002
Log simulated likelihood	-2179.019
Chi2(2)	470.02
Prob > chi2	0.0000
BIC	4836.15
AIC	4466.04

bikes or scooters are more likely to use e-bikes than those without. E-scooters have a comparable impact, with a relative risk of 1.195 if the user has access to micro-mobility mode. This is similar to the conclusions of [19] that access to micro-mobility also correlates with shared mobility usage within each scheme.

All variables are significant at the 99% level for the frequency of using shared micro-mobility choices in the case of e-bikes. Travelers who use shared micro-mobility daily have a risk ratio of 3.937 to use shared e-bikes and 7.787 to use shared e-scooters compared to those who use micro-mobility weekly. Travelers who use shared micro-mobility monthly have a risk ratio of 2.179 to use shared e-bikes and 1.289 to use shared e-scooters more than those who use micro-mobility weekly. Finally, travelers who do not use shared micro-mobility have a risk ratio of 0.697 to use shared e-bikes compared to those who use the shared micro-mobility weekly. At the same time, it is found that using the shared e-scooters is not significant for this comparison.

3) FOR THE EDUCATION VARIABLE

In the case of e-bikes, the probability of using e-bikes for travelers who are in high school and undergraduate studies is lower than those travelers' who are in graduate studies, with risk ratios of 0.526 and 0.728, respectively. This is in line with Reck and Axhausen's [19] results that college students are more likely to use shared e-bikes in Zurich, Switzerland, as well as in Palermo, Italy [20], and in Texas, US [27]. In the case of e-scooters, the relative risk ratios of high school and undergraduate studies are 0.645 and 0.829, respectively, compared to graduate studies (high school and undergraduate students are less likely to use e-scooters than graduate students).

4) FOR JOB AND INCOME VARIABLES

Part-time workers are 1.209% more likely to ride a shared e-bike than full-time workers, while the risk ratios for the self-employed and students are 0.346 and 0.6473, respectively. In the case of shared e-scooters, the relative risk for students, unemployed, and retired are 0.770, 0.433, and 0.266, respectively, compared to full-time employment. Therefore, full-time workers are more likely to use shared e-bikes and shared e-scooters than others, which is partially similar to previous results indicating that full-time workers positively influence shared e-bike use [17], [19]. It was found that the travelers' behavior of micro-mobility is similar between Zurich and Budapest in the case of shared e-bikes, while it is somehow different in the case of shared e-scooters. This could be explained by the heavier usage of shared e-scooters in Zurich compared to Budapest, which is more dependent on shared bikes. Regarding income, the probability of using shared e-bikes or shared e-scooters by low-income people are higher than high-income ones by a risk ratio of 1.505 and 1.743, respectively, which is in line with the results of [22] and [25].

5) FOR TRIP PURPOSES VARIABLE

We agglomerate the work, shopping, educational, and home trip purposes together for the better significance of the model. Compared to leisure trips, the risk ratio of these trip purposes is 1.520 for using e-bikes. (i.e., the probability of using e-bikes for other trips rather than leisure trips are higher). The risk ratio for e-scooters is 1.325 compared to leisure trips. Both of the variables are significant at a 95% level.

6) FOR GENDER AND AGE VARIABLES

Likely to trip purposes, we divided the age categories into two groups; lower than 44 years old and equal and greater than 44 years old for the better significant model. In the case of e-bikes, travelers over 43 years old have a risk ratio of 0.784 compared to travelers below 44 years old. In the case of e-scooters, the probability of using e-scooters for travelers over 43 years old is lower than for people younger than 44 years with a risk ratio of 0.379, which is similar to the findings of [22] and [27]. Both variables are significant at a 95% level. Male travelers are 1.225 higher than females to use e-bikes, while it is 1.176 in the case of e-scooters, which is in line with previous findings that females are less likely to use micro-mobility [17], [19], [22].

Ignoring the observed variables, the alternative specific constant ($\beta 0$) presents the relative risk ratio of choosing one alternative, such that the relative risk ratio of using shared e-bikes and shared e-scooters over conventional shared bikes is 0.751 and 0.472, respectively. To that end, travelers are less likely to utilize shared e-bikes and shared e-scooters and more likely to ride conventional shared bicycles.

B. MARGINS AND VALIDATION

A commonly used method for validating discrete choice models involves the calculation of elasticities, e.g., marginal effects, which serve as measures of size effect and are considered policy-related values, based on Parady et al. [67] research, as well as Ziliak and McCloskey [68]. The marginal effects focus on the magnitude of effects and the estimation of values that hold interpretability in a policy context.

The model's predictive margins indicate that the estimated likelihoods of choosing conventional shared bikes, shared e-bikes, and shared e-scooters are 40.1%, 38.6%, and 21.3%, respectively, at a 95% confidence level (Figure 2).

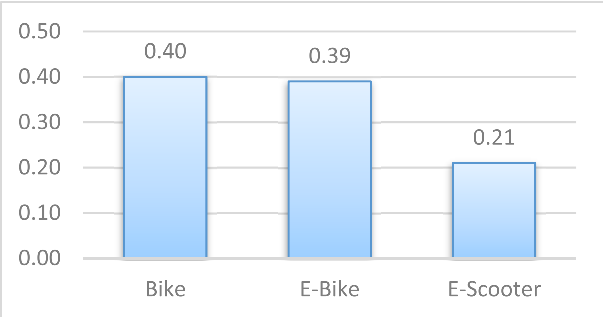


FIGURE 2. **The model's predictive margins.**

The observed preference for conventional bikes could be attributed to several factors. Firstly, personal choice and familiarity with traditional bikes might influence users' decision-making. Some individuals may prefer the physical exertion and exercise associated with pedaling a conventional bike. Secondly, it is possible that the accessibility to conventional bikes was better in the study area compared to e-bikes, making them a more convenient option for users. However, it is important to note that our study primarily aimed to investigate and understand the relative importance of different attributes influencing micro-mobility mode choices rather than promoting any specific mode.

Figure 3 illustrates that a 20% change in travel time of conventional shared bikes results in a shift in the margins of bikes, e-bikes, and e-scooters. Furthermore, as shown in Figure 3, a 20% increase in the trip cost and walking time of conventional bikes causes a shift in the margins of bikes, e-bikes, and e-scooters. According to the companions (Figure 2), the margins for e-bikes and e-scooters increase when the trip cost, trip time, and walking time increase, whereas the margins for bikes fall when the trip time increases.

Figures 4-6 show how parking type affects margins. The margins are significant at 95% confidence and 6% standard error. Figure 4 shows how shared e-bike parking affects margins. When a traveler mainly uses free-floating parking, shared e-bikes, shared bikes, and shared e-scooters have margins of 44%, 37%, and 19%, respectively. This margin is based on e-bikes' changing qualities while opponents' remain unchanged. Shared e-bikes have the highest margin in free-floating and shared bikes in parking lots.

Figure 5 displays margin variations for shared conventional bike parking types. When a traveler primarily uses free-floating parking, shared e-bikes, shared bikes, and shared e-scooters have margins of 35%, 46%, and 19%. This margin is dependent on bike characteristics while opponent modes are held constant. Free-floating shared bikes have a higher margin than shared e-bikes in parking lots.

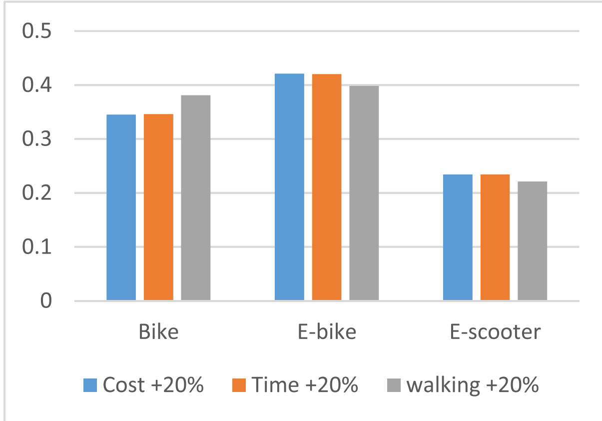


FIGURE 3. **The predictive margins of the model at 20% increment in the trip cost, trip time, and walking time of shared conventional bikes.**

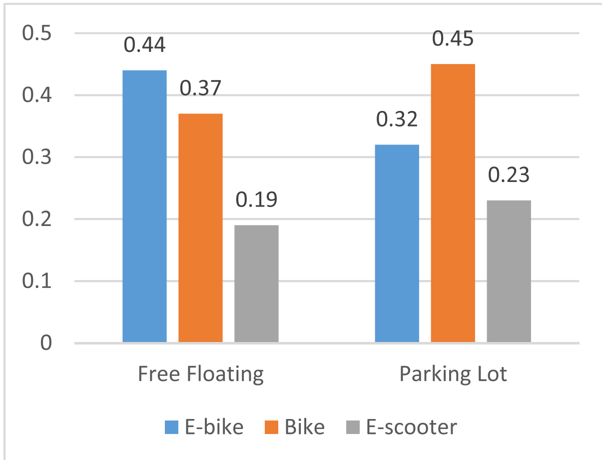


FIGURE 4. **The predictive margins when the parking type is possible for e-bikes.**

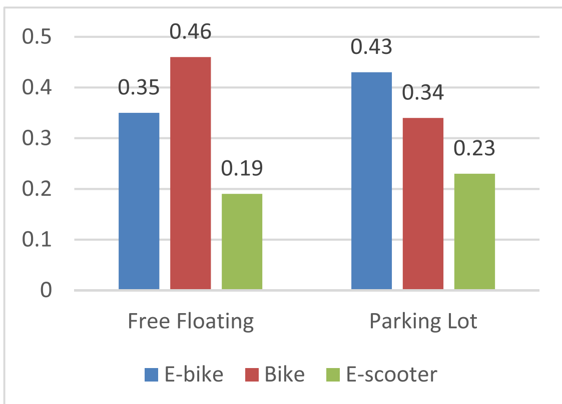


FIGURE 5. **The predictive margins when the parking type is possible for bikes.**

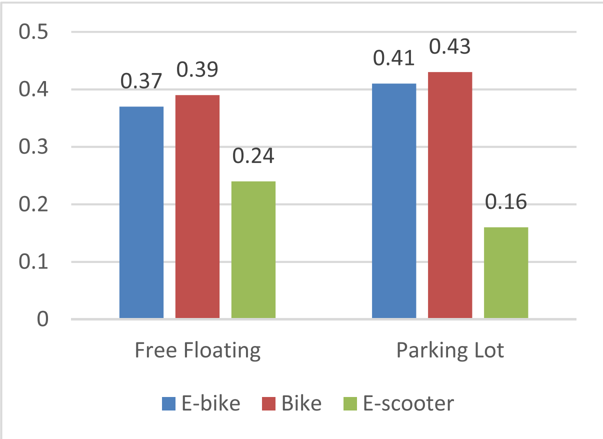


FIGURE 6. **The predictive margins when the parking type is possible of e-scooters.**

Figure 6 displays margin changes for shared e-scooter parking types. Shared bikes and shared e-bikes have better margins than e-scooters. This margin is based on shared e-scooter attributes versus opponent micro-mobility modes.

In summary, preliminary data show the margin of changing transport mode attributes while choosing parking type (Figure 4-6). According to the margins in the preceding figures, shared bikes and shared e-bikes are superior to shared e-scooters.

This study offers the margins of use based on the created model and the transport mode variables. Shared bikes have the largest margin, while shared e-scooters have the lowest. There is also a slight variation in margins between conventional shared bicycles and shared e-bikes. The results show how trip time, time spent walking, and trip cost influence users' decisions. The highest chance of switching to shared e-bikes is reached when the travel time or the travel cost increases by 20%, or when the travel time or walking time increases by the same proportion for shared bikes (Figure 3). As a result, the likelihood of picking shared bicycles varies based on the parameters of the trip and can be swapped out for the second-most-popular alternative, shared electric bicycles. It's determined that all three types of transportation benefit from free-floating parking.

VI. CONCLUSION

A stated preference survey using discrete choice examination was conducted, and an ML model was developed to examine how people use shared bikes, shared electric bikes, and shared electric scooters in urban areas with travel time between 15 and 25 minutes. Job, age, income, gender, travel purpose, and level of education were considered. The attributes of the options were trip time, cost, walking time, and the type of parking. The developed model estimated the extra cost/benefit of parking-based transportation options. The data shows that consumers prefer to ride shared bicycles, while the likelihood of selecting a shared e-scooter is the lowest. Micro-mobility customers benefit most from the freedom of the free-floating option.

The results underscore the potential to attract more shared electric micro-mobility users through the policies or incentives of decreasing the walking time, which indicates increasing the density of these modes in the urban context. The likelihood of choosing a transport mode with a parking lot is 40% lower than the probability of free-floating parking. It's determined that all three types of micro-mobility modes benefit from free-floating parking. Furthermore, it was found that the travelers' VOT is 2010 HUF (∼5 EUR) per hour. Other findings were as follows: car drivers prefer e-bikes and e-scooters more than other travelers; users who have access to or frequently use micro-mobility have a higher probability of using shared electric micro-mobility; graduate students and full-time workers have a higher likelihood to use shared e-bikes and shared e-scooters. In addition, leisure trips are not the highest motivation to use the shared electric micro-mobility; males have a higher probability of using shared e-bikes and shared e-scooters. Finally, elderly travelers are less likely to use the shared electric micro-mobility. The shared electric micro-mobility options require more effort and policies to be employed as shared conventional bikes sound more attractive to the users. The highest chance of switching to shared e-bikes is reached when the travel time or the travel cost increases by 20%, or when the travel time or walking time increases by the same proportion for shared bikes.

To employ the research findings effectively, stakeholders may implement the following strategies: 1) Design a dense network of shared micro-mobility stations, reducing walking time. 2) Develop marketing campaigns and initiatives tailored to attract non-student, female, and older individuals. Address their unique needs, concerns, and preferences to facilitate their adoption of shared electric micro-mobility. 3) Address safety and privacy issues associated with shared electric micro-mobility systems. Invest in robust security measures, such as secure user data management and privacy protection protocols, to build trust and confidence among potential users. 4) Partner with local authorities to influence policy development and ensure supportive regulations for shared electric micro-mobility. This could involve advocating for infrastructure improvements, dedicated bike lanes, and integrating existing public transportation systems. These practical implications will drive industry growth and contribute to sustainable urban transportation solutions.

While this study focuses on micro-mobility modes in Budapest, Hungary, the findings and insights can have broader implications and applicability. The factors influencing user choices, such as trip time, trip cost, walking time, and parking preferences, are fundamental considerations in designing and implementing micro-mobility systems worldwide. By understanding these factors and their relative importance, decision-makers in other countries and regions can gain valuable insights into the preferences of shared electric micro-mobility users, allowing them to tailor their strategies and policies accordingly. Moreover, the methodology employed in this study, using a discrete choice modeling survey, can serve as a framework for similar investigations, facilitating comparative analyses and the expansion of micro-mobility services.

Future research will consider safety, privacy, and security aspects and focus more on the rural context and travelers' behavior, as well as another one that could deal with a comprehensive comparison between different modeling methods, including Machine Learning and ANNs, which is a valuable avenue for future investigation. Such a study could shed further light on the comparative performance of various approaches and provide valuable insights into the strengths and limitations of different models.

APPENDIX

There are 48 questions in this survey.

1. The picture above shows the three options of regular bikes, electric bikes, and electric scooters, respectively.
2. These three options are called Shared Micro-Mobility modes which are either provided by public or private companies.
3. You can use them by booking your preference that is close to your location using an application on your mobile.

What is the main mode of transportation do you mostly use to get to your usual main destination on an ordinary day?

- Bike or Scooter Sharing
- Own Bike or Scooter
- Car as driver
- Car as passenger
- Public transport (tram, metro, bus, train)
- Taxi
- Walking
- Other

Do you have access to a bike or scooter? *

- Both
- Only Bike
- Only Scooter
- None

How frequently do you use shared micro-mobility modes?

- Never
- Monthly
- Weekly
- Daily

If you already used or you are willing to use Shared Micro-Mobilityin traveling to your main destination on an ordinary day, to what extent do the following aspects influence your choice of shared micro-mobility? (1 is low importance, and 10 is high importance).

	1	2	3	4	5	6	7	8	9	10
Distance to the nearest Bike/ Scooter										
Transport cost										
Safety										
Traffic congestion										
Weather condition										
Distance to Parking Lot (Docking Station)										

Assuming you use the Shared Micro-Mobilitysystem on an ordinary day, which of the following is most likely your main destination?

- Work
- Education
- Shopping
- Home
- Leisure or others

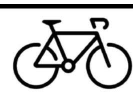
Answer all questions in this survey ignoring the effect of Pandemic (COVID-19),

In the following six questions, it is needed to choose your preference of (regular bikes, electric bikes, and electric scooters) among the different situations (attributes) based on:

1) Trip time (Without including walking time)
2) Trip cost,
3) Parking type
4) Walking Time

Tips:

1. **Free-Floating**: you leave the transport mode **anywhere** close to your destination.
2. **Parking Lot**: you should leave the transport mode to the nearest parking lot to your destination **(Docking Stations)**.
3. Walking Time: The time spent out of the vehicle by walking from your place to the bike or scooter, and the time spent walking to your destination after leaving the bike or the scooter.
4. 1 EUR = 400 Ft.

			
	Bike	**E-Bike**	**E-Scooter**
Trip Time (minute)	**20**	**15**	**15**
Trip Cost (Ft.)	**400**	**750**	**600**
Walking time (minute)	**8**	**6**	**4**
Parking Type	**Parking lots**	**Parking lots**	**Parking lots**

- E-Bike (Shared electric Bike)
- Bike (Regular Shared Bike)
- E-Scooter (Shared electric Scooter)

	Bike	E-Bike	E-Scooter
Trip Time (minute)	25	20	15
Trip Cost (Ft.)	400	400	400
Walking time (minute)	6	8	8
Parking Type	Free floating	Parking lots	Free floating

- E-Bike (Shared electric Bike)
- Bike (Regular Shared Bike)
- E-Scooter (Shared electric Scooter)

	Bike	E-Bike	E-Scooter
Trip Time (minute)	20	25	20
Trip Cost (Ft.)	750	400	400
Walking time (minute)	4	4	6
Parking Type	Free floating	Free floating	Parking lots

- E-Bike (Shared electric Bike)
- Bike (Regular Shared Bike)
- E-Scooter (Shared electric Scooter)

	Bike	E-Bike	E-Scooter
Trip Time (minute)	15	20	25
Trip Cost (Ft.)	750	600	600
Walking time (minute)	8	8	6
Parking Type	Parking lots	Parking lots	Parking lots

- E-Bike (Shared electric Bike)
- Bike (Regular Shared Bike)
- E-Scooter (Shared electric Scooter)

	Bike	E-Bike	E-Scooter
Trip Time (minute)	25	15	25
Trip Cost (Ft.)	600	600	750
Walking time (minute)	4	4	4
Parking Type	Parking lots	Free floating	Free floating

- E-Bike (Shared electric Bike)
- Bike (Regular Shared Bike)
- E-Scooter (Shared electric Scooter)

	Bike	E-Bike	E-Scooter
Trip Time (minute)	15	25	20
Trip Cost (Ft.)	600	750	750
Walking time (minute)	6	6	8
Parking Type	Free floating	Free floating	Free floating

- E-Bike (Shared electric Bike)
- Bike (Regular Shared Bike)
- E-Scooter (Shared electric Scooter)

Socio-demographic information

Gender: *

- Female
- Male
- Others

Age: *

Average monthly net income (excluding taxes)?

- Less than 50,000 ft (150 Euro)
- 50,000 ft (150 Euro) - 100,000 (300 Euro)
- 100,000 ft (300 Euro) - 150,000 (500 Euro)
- 150,000 ft (500 Euro) - 200,000 (650 Euro)
- 200,000 ft (650 Euro) - 250,000 (800 Euro)
- 250,000 ft (800 Euro) - 300,000 (950 Euro)
- 300,000 ft (950 Euro) - 350,000 (1100 Euro)
- 350,000 ft (1100 Euro) - 400,000 (1250 Euro)
- More than 400,000 ft (1250 Euro)
- I prefer not to answer

Job:

- Full-time worker
- Part-time worker
- Student
- Retired
- Unemployed
- Self-employed
- Other

Education level? *

- High school
- Undergraduate studies
- Graduate studies (MA, M.Sc., PhD, etc.)
- Other

Thank you for completing this survey.

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AHMED JABER was born in Amman, Jordan, in 1992. He received the B.S. and M.S. degrees in transportation engineering from An-Najah National University, Nablus, Palestine, in 2019. He is currently pursuing the Ph.D. degree with the Faculty of Transportation Engineering and Vehicle Engineering, Budapest University of Technology and Economics.

He is also a Researcher with the Faculty of Transportation Engineering and Vehicle Engineering, Budapest University of Technology and Economics. He was a Project Coordinator with the World Bank Project, Ministry of Local Government in Palestine, and a transportation and urban planning engineer at a consultant company. Overall, he has more than eight year's experience in transportation fields. He has published and peer-reviewed more than 40 articles in high-ranked journals. His master thesis was related to the pedestrian safety, while his Ph.D. thesis is related to the micro-mobility travel modeling.

JAMIL HAMADNEH received the Ph.D. degree in transportation engineering and technology from the Faculty of Transportation Engineering and Vehicle Engineering, Budapest University of Technology and Economics, Hungary. He is currently an Assistant Professor with Palestine Technical University-Kadoorie, Tulkarem, Palestine. He was a Transportation Engineer with Traffic Higher Council, Ramallah, Palestine. His research interests include autonomous vehicle, activity chain optimization framework, sustainability, travel behavior, the multitasking on board of transport modes, the impacts of new technologies on the mobility of people and land-use, and the social acceptability of future transport technologies.

BÁLINT CSONKA received the Ph.D. degree in transportation technology science in the topic of development of electro mobility services from the Budapest University of Technology and Economics, in 2020. He is currently a Research Associate with the Budapest University of Technology and Economics. His research area is the development of methods to support the operation of electric vehicles and charging infrastructure, and the optimization of local energy production and storage capacities. He has published and peer-reviewed more than 100 articles in high-ranked journals. He is the Co-Founder of Bolley Company.