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People Preferences Towards Bikes and Electric Bikes in Urban Areas – Case Study for Hungary

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ABSTRACT

In the last decade, innovations in micro-mobility (i.e. lightweight vehicles) have been developing fast. Travellers switch to more efficient, affordable, economical and eco-friendly transport modes as a cultural, habit and policy compliance to reduce the dependence on motorised transport modes. In this research, the behaviour of travellers toward two types of bikes: (1) electric bike (e-bike) and (2) regular bike (bike) is predicted. A mathematical model of transport mode choice is developed using the discrete choice modelling approach based on a stated preference (SP) survey distributed in Hungary. The developed transport choice model includes trip cost, trip time and walking distance to reach the location of bike/e-bike or to reach your destination after parking your bike/e-bike, parking type, economic, sociodemographic and travel variables. The developed model shows that travellers are more likely to choose bikes over e-bikes. Significant variables demonstrate influence on travellers in choosing bikes or e-bikes, such as parking type, which emphasises that free-floating parking is preferred over parking lots. This research adds value to the literature that emphasises the importance of parking type, trip purpose and other sociodemographic variables in choosing bikes/e-bikes in urban areas.

KEYWORDS

e-bike; transport mode choice; multinomial probit logit model; travel behaviour.

1. INTRODUCTION

The world has moved towards eco-friendly transport modes to save the environment and create a sustainable transport system [1]. The development of the transport system in the presence of technology leads to changes in the travel mobility of people. Travellers select transport modes based on their preferences considering the available transport modes and the regulations that govern that area [2]. The economic theory shows that people always try to maximise their utilities by minimising travel time when they travel (i.e. travelling is not an activity, it is partially or fully considered a waste) [3]. Guevara [4] demonstrates based on his study that the waiting time is the unfortunate part among the other parts of travel (i.e. walking time and trip time). Utility maximisation in travel can be realised by using eco-friendly transport modes. The eco-friendly transport mode consists of several motorised and not motorised types, such as bikes, autonomous vehicles, carpooling, car sharing, electric cars, public transport, electric bikes and electric scooters [5-7].

In this paper, a focus is given to the preferences of people towards bikes, which are eco-friendly transport modes. The case study is Budapest, which has a good infrastructure for bikes and is considered one of the cities with the most bike users in Europe [8-10]. The development and innovation of micro-mobility is so helpful for policymakers and operators, such benefits are fostering health, reducing congestion, opening new business opportunities and developing green cities [11]. In the literature, many studies focus on conventional transport modes, and specific types of micro-mobility types due to their availability in the market. With the fast development of technology, smart and updated technology has integrated with the existing transport modes to develop new ecofriendly shape of transport modes, such as electric bikes, electric scooters and others. The attention to the travellers' behaviour in electric micro-mobility time needs more research because it is impacted by the introduction of new shapes or designs of transport modes. Moreover, micro-mobility is impacted by the people across geographical areas, for example, topography changes affect the use of conventional micro-mobility, such as bikes and scooters [12].

In the paper, a focus is given to two types of micro-mobility (hereinafter also called soft transport modes): regular bikes and electric bikes. The objective of this work is to study the behaviours of people towards these two types that are commonly spread on streets as shared bike/e-bike. To model the behaviour of travellers, a set of variables are needed, such as trip, time of trip, walking distance to reach the location of bike/e-bike or to reach a destination after parking bike/e-bike and parking type. Moreover, the impact of economic and socio-demographic variables on preferences of people on choosing a transport mode (i.e. bike/e-bike) is examined. The trip characteristics are examined to show their effects on choosing a transport mode, such as trip purpose and current transport mode of a traveller. The aim is to analyse the travel behaviour of travellers in urban areas during their trips to their frequent main destinations. A traveller is asked to select one of the two soft transport modes: shared electric bike (e-bike) and shared regular bike (bike). Travellers are asked to choose a soft mode based on four factors: trip cost, trip time, access times to and from the location of a soft transport mode and parking type at the end of a trip (i.e. docked or dockless).

The contribution of this research is to model the traveller preferences towards two dominant soft transport modes in Budapest. A lack of research is found in the literature that studies the preferences of people for shared bikes and shared electric bikes. Moreover, the focus of this study is whether travellers travel to their frequent and main trips by soft modes. The research aims to find the pertained factors that affect using e-bikes and bikes positively and negatively. The result of this research is beneficial for operators to improve their service or extend their work. It is worth mentioning that the European Union leads towards more sustainable eco-friendly transport modes that improve mobility, equity and social welfare [13]. The choice of the two soft transport modes is conducted where some characteristics are shared, such as the used road infrastructure and operating methods (mobile application).

The current paper includes the introduction in section one, and the literature review is in section two. Section three presents the used tools and methods in conducting the research. Section four shows the results, while section five presents a discussion of the findings. Section six presents the conclusion of the research.

2. LITERATURE REVIEW

Travel time in time allocation theory is often seen as wasted time [12]. Travellers plan their journeys to reduce this waste, multitask on board or seek beneficial experiences. Travel time is viewed as a cost rather than a benefit, and people often use this time for enjoyable activities like using social media or sleeping. Research indicates that people when they aim to travel, seek to pay more to avoid discomforts such as waiting, seating issues and crowding. The value of travel time varies across factors like multitasking ability, use of information and communication technologies (ICTs), trip destination, mode of transport, demographics, journey conditions, timing and geographic location [14]. Studies show that minimising the value of travel time (VOT) costs less than infrastructure improvements, such as providing pleasant travel onboard through an efficient public transport system, costs less than constructing a new lane or bridge [15, 16]. People prefer to switch to new transport modes if comfort and convenience are enhanced. Travel behaviour varies by individual and can change over time due to external factors. High-income travellers and those who face difficulties in travelling are more willing to pay for time savings compared to children, the retired, the elderly or the unemployed. People aim to reduce travel time unless the onboard condition supports productive multitasking [17].

Micro-mobility (i.e. electric bikes (e-bikes) and regular bikes) has become a significant focus in urban transport research due to its potential to offer sustainable and efficient travel options. Several studies have explored various aspects influencing the adoption and usage of these modes. Reck et al. [18] applied a multinomial logit model to check how the travel distance, vehicle density, location, time of day and battery capacity impact commuters when they use electric bikes and scooters. Their study, which did not consider demographic characteristics, aligns closely with the present research, focusing on similar micro-mobility usage factors. Building on this, Reck et al. [19] applied a mixed logit model to assess the environmental effects on shared micro-mobility. Their findings present that weather significantly impacts micro-mobility choices, excluding variables like travel time, cost of travel and walking time. Furthermore, the findings underline the importance of environmental factors, which are relevant to understanding bike and e-bike preferences in urban areas. Rayaprolu and Venigalla [20] employed logistic regression to show that different forms of micro-mobility are used variably based on motivation and trip distance. They identified safety as a major concern and cost as a significant positive factor. This emphasises the need to consider safety and economic aspects in micro-mobility studies. Reck and Axhausen [21] developed a multinomial probit model incorporating demographic data, revealing that shared micro-mobility users of Zurich are young, male, university-educated professionals living in affluent, single-person households. This demographic profile is pertinent to understanding the potential user base for micro-mobility services. Campisi et al. [22] used an ordinal logit model to analyse the impacts of travellers, transport modes and journey variables on shared micro-mobility, such as variables as population, car ownership, infrastructure service, traveller safety perception, comfort and environment. Their results indicate that as car ownership and age are increased, the willingness to use shared micro-mobility is decreased. This study highlights the significant influence of infrastructure and demographic factors on mode choice. Zhao et al. [23] compared machine learning and logit model results in order to choose the preferred transportation mode. They compared cars, bikes, public transport and walking modes. They concluded that logit models outperformed machine learning techniques, underscoring the effectiveness of logit models in transport mode choice studies, including this one. Kutela et al. [24] utilised Bayesian networks to study preferences for shared micro-mobility, focusing on factors like cost, walking time, accessibility, frequency, motivation and occupation. Their work directly relates to understanding the multifaceted factors influencing bike and e-bike preferences in urban settings. Bai and Jiao [25] showed the importance of green space and commercial locations through GIS spatial analysis. They emphasised the positive correlation between green space and commercial locations with electric scooter usage. These environmental factors are also applicable to bike and e-bike usage, suggesting that urban planning should consider such elements to promote micro-mobility. Caspi et al. [26] applied geographically weighted regressions, and they showed that students are the main users of shared electric scooters. This demographic insight is valuable for targeting specific user groups in promoting micro-mobility. Hatami et al. [27] used the random forest approach to model the choice between active mobility and public transport, stressing the importance of sustainable transport modes like electric bikes. Their findings support the inclusion of diverse analytical methods to better understand mode choice. Elhenawy et al. [28] highlighted that shared policies have costs, but customer incentives help cover these relevant for understanding the economic aspects of micro-mobility services. Jaber et al. [29] focused on the users' preferences of micro-mobility in urban areas, specifically shared micro-mobility. The authors employed a discrete choice modelling approach to develop a transport choice model evaluated through a multinomial logit (MNL). This underscores the need for effective policy and economic strategies to encourage the adoption of shared electric micro-mobility.

These studies collectively focus on modelling micro-mobility, such as scooters and bikes, to examine the differences in terms of availability and cost between shared electric modes. This research aims to predict and model travel behaviour for short urban trips, based on variables such as trip time, trip cost, walking distance and parking type, as well as examining the preferences of people across socio-demographics and micro-mobility ownership. This approach helps reveal preferences for shared and electric micro-mobility modes.

3. DATA AND METHODS

Travellers choose soft modes when they travel based on their preferences. The available soft modes for them are personal and shared. Based on economic theory, a traveller tries to maximise his/her utility in travelling. The preferences of a traveller are summarised in several factors relevant to the traveller himself/herself and the travel characteristics. In this work, a traveller's behaviour is studied toward two soft modes, e-bikes and bikes. An SP survey is used to collect travellers' respondents on a discrete choice experiment (DCE). Travellers record their travel characteristics and their sociodemographic variables. *Figure 1* presents the methodology for conducting this research. The first part is distributing the SP survey that includes the DCE and the sociodemographic variables. The second part is applying random utility theory in analysing the DCE through one of the logistic models of the random discrete choice modelling approach [30].

The variables that impact traveller decisions in choosing bikes and e-bikes are selected based on literature and the experience of the authors as well as the case study area, Budapest, Hungary. The variables are travel time, travel cost, walking to and from the location of the bike/e-bike and the parking type.

The discrete choice modelling is used to estimate the value of certain attributes for travellers, and this is done by asking travellers to choose between a bike and an e-bike based on different situations as in *Table 2* [31]. The DCEs in this study reflect two cases, the existing and the proposed problem [32]. The DCE gives information on the willingness to pay for a travel option [32]. In this work, an SP survey method is utilised to collect responses from travellers where preferences, priorities and the relative importance of travellers' features connected to the transport mode are realised [30].

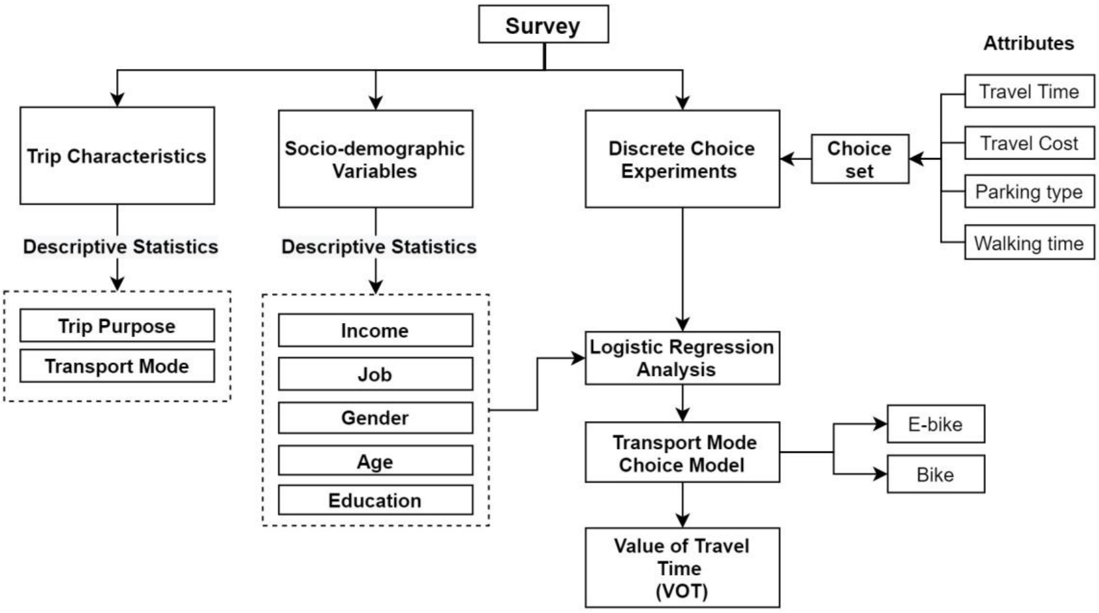

Figure 1 – The methodological approach

3.1 DCE design

Two transport options/alternatives are included in the DCEs (i.e. bikes and e-bikes). The attributes/factors associated with each alternative are time, cost, walking time and parking type as shown in *Table 1*. The SP survey is distributed in Budapest, Hungary. In the DCE part, travellers have to choose one alternative from a choice combination in a block of 6 choice combinations based on respondents' preferences. The values of attribute levels are selected to let respondents make a trade-off decision between the alternatives. *Table 1* shows the attributes and levels design of the choice sets.

Table 1 – DCE's attributes values

Levels	Attributes			
	Parking type	**Total walking time (minute)**	**Total trip cost (HUF)***	**Total trip time (minute)**
L 1	Free floating	1.30 * waiting time	1.30 * trip cost	1.25 * trip time
L 2	Parking lots	waiting time	TC	TT
L 3		0.7 * waiting time	0.70 * trip cost	0.75 * trip time

1 euro=400 HUF

Table 2 presents an example of one choice combination from the survey that a respondent had to answer. A respondent, as mentioned earlier, has to answer 6 choice combinations. A respondent who chooses a bike is impacted by parking type and trip time, on the other hand, a traveller who chooses an e-bike is impacted by cost and walking time variables. The importance of factor/attribute is impacted by preferences of a traveller and other relevant variables like income.

Table 2 – One choice combination

	 E-bike	 Bike
Total trip time (minute)	20	15
Total trip cost (HUF)	400	600
Total walking time per trip (minute)	6	8
Parking type	Parking lots	Free floating

In the DCE, the respondents were asked to answer one block which contains 6 choice combinations. It is worth mentioning that fractional factorial design is used to avoid a high number of choice sets for each respondent [33]. Each choice set has two alternatives where the number of attributes and the levels are equal in each block. The fractional factorial design is applied by RStudio to produce the concrete combinations. It is noted that a block is randomly distributed to a respondent [34]. The “Lma.design” function from the “support.CEs” package is used to create the DCEs from the orthogonal main-effect array. The sample size should be at least 187 for conducting the analysis [35]. Stata Software 16.1 is used in the analysis. The LimeSurvey platform is used in distributing the survey where the random distribution of blocks is maintained [36].

3.2 Multinomial probit logit model

It is scientifically known that an individual is a rational decision-maker based on the random utility theory where travellers make decisions to maximise their utilities [37]. The probability that a traveller (i) selects one alternative (j) over the others is possible to be estimated. This is given in *Equation 1*

$$P(\mathrm{c}_{ij}/\mathrm{C}) = \mathrm{P}(U_{\mathrm{c}_{ij}} > U_{ik}) \,\forall\, k \neq j, k \in C \tag{1}$$

where P (c_{ij}/C) stands for the probability of an individual (i) selecting an alternative (j) from the choice set (c), C means the choice sets for a traveller, U_{cj} stands for the perceived utility of choosing an alternative (j) from the choice set c [37]. The utility function includes two parts, a deterministic and a stochastic part, as given in *Equation 2*

$$U_{ij} = V_{ij} + \varepsilon_{ij} \tag{2}$$

where V stands for the deterministic part, and ε stands for the stochastic part. The deterministic part models the travellers’ mean perceived utility when selecting an alternative [37]. The random part models the unknown deviation of the travellers’ utility from the mean value, and it captures the uncertainty in the choice modelling [37]. ε_{ij} is an abbreviation for a random error, independent and identically distributed (IID) extreme value type 1 (i.e. Gumbel distribution) across all alternatives, individuals and choice situations. Both β_i and ε_{ij} are considered stochastic parameters, and they are not observed directly [38].

The probability that an individual (i) chooses alternative (j) is given by *Equation 3*:

$$P_{ij} = P(V_i = \text{j}) = \phi(\beta_0 + X_{ij}\beta_n) \tag{3}$$

where ϕ is the cumulative standard normal distribution function.

3.3 Model specifications and design

The developed multinomial probit choice model is formulated based on the result of analysis, as shown in *Equation 4*. The model shows how travellers prefer to select a transport mode over others and the impact of traveller and travel variables on the choice of a transport mode (i.e. utility function);

$$\begin{aligned} U_{ijc} = {} & \beta_{o\,(i)} + \beta_{TC\,(i)} * TC + \beta_{TT\,(i)} * TT + \beta_{WT\,(i)} * WT + \beta_{PT\,(i)} * PT\ (Dummy) \\ & + \beta_{Tranport\ mode\ (i)} * The\ regular\ used\ tranport\ mode\ (Dummy) * Dummy_j \\ & + \beta_{education(i)} * education\ (Dummy) * Dummy_j + \beta_{Gender(i)} \\ & * Gender\ (Dummy) * Dummy_j + \beta_{Trip\ purpose\ (i)} * Trip\ Purpose\ (Dummy) \\ & * Dummy_j + \beta_{Age\ (i)} * Age\ (Dummy) * Dummy_j + \beta_{Occupation\ (i)} \\ & * Occupation\ (Dummy) * Dummy_j + (\varepsilon)_{ijc} \end{aligned} \tag{4}$$

where U_{ijc} represents the utility of alternative (j) chosen by individual (i) at time c, TC is the travel cost, TT is the trip time, WT is the walking time and PT represents the parking type.

$\beta_{o\,(i)}$, $\beta_{TC\,(i)}$, $\beta_{TT\,(i)}$, $\beta_{WT\,(i)}$, $\beta_{PT\,(i)}$, $\beta_{Transport\ mode\ (i)}$, $\beta_{education(i)}$, $\beta_{Age\ (i)}$, $\beta_{Gender(i)}$, $\beta_{Job\ (i)}$, $\beta_{trip\ purpose(i)}$, $\beta_{Age\ (i)}$, and $\beta_{occupation\ (i)}$ are parameters of the observed variables to be estimated from the collected data, and ε is an indeterministic error. Each case-specific variable is multiplied by the dummy of the alternative. The regular transport mode stands for the transport mode used by the respondents to reach their main trip purpose. The VOT is represented in *Equation 5* [39, 40].

$$VOT = \frac{\beta_{tt}}{\beta_{tc}} \tag{5}$$

3.4 Budapest as a case study

Budapest's transportation system has evolved to accommodate various modes of transport, with a growing focus on sustainable mobility solutions like cycling. In recent years, the city has made significant investments in bike-sharing programs and cycling infrastructure as part of its effort to reduce traffic congestion and promote eco-friendly alternatives. *Figure 2* shows the Budapest road network where bike stations are marked in green dots.

The MOL Bubi bike-sharing system, which launched in 2014, is an essential element of Budapest's green mobility strategy, as well as the Donkey's Republic. Research has shown that the availability of cycling infrastructure, such as dedicated bike lanes and accessible parking facilities, positively influences the frequency and preference for bike usage in urban areas [25, 41]. In line with broader European trends, Budapest has adopted policies that prioritise cycling, particularly in its central districts where traffic density is highest [12].

The map shown in *Figure 2* provides a detailed spatial representation of Budapest's bike-sharing infrastructure, specifically highlighting the locations of bike stations across the city's districts. This map aligns with the ongoing shift towards sustainable transport, illustrating a concentration of bike-sharing hubs in the city centre, which coincides with areas of high demand for short-distance travel. Central Budapest has more bike-sharing stations, supporting findings from studies that suggest bike usage is higher in densely populated and economically active zones where cycling offers a time-efficient and low-cost alternative to other modes of transport [26]. These bike-sharing stations, clustered around the city's core, highlight Budapest's efforts to cater to commuters and tourists who rely on bikes for their daily mobility needs.

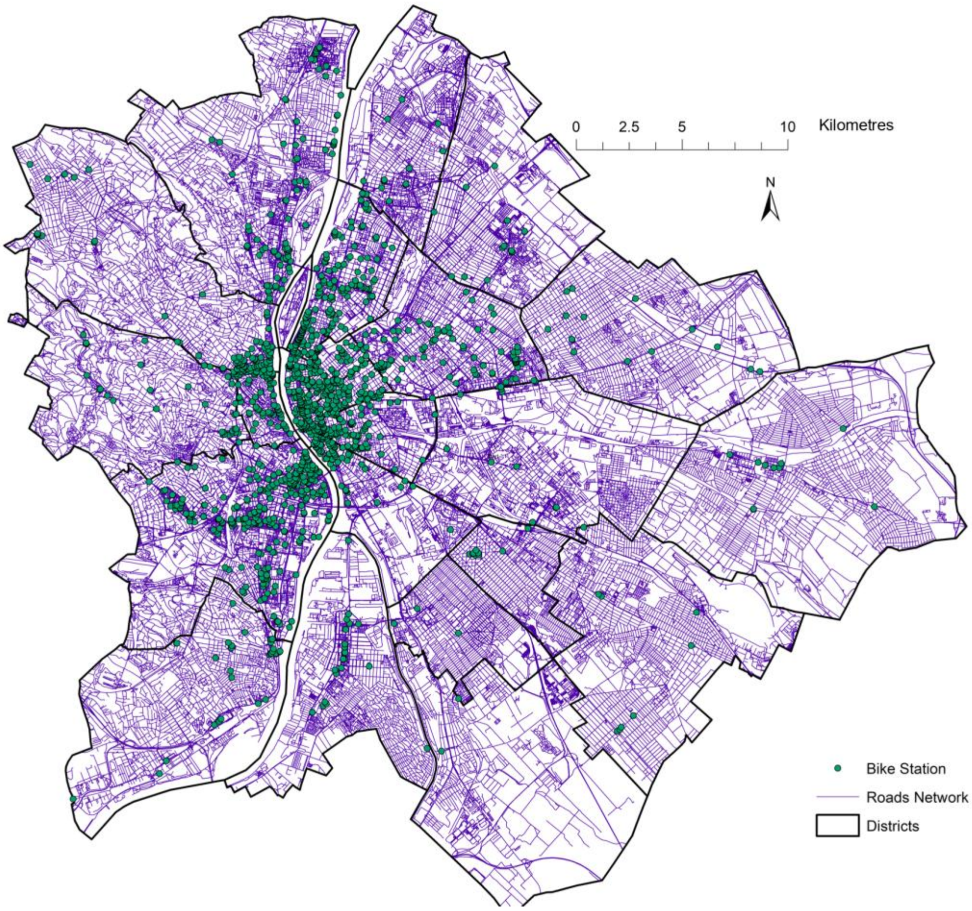

Figure 2 – Budapest road network

The distribution pattern seen in the map also reflects research indicating that cycling infrastructure tends to be concentrated in areas with better road networks and higher urban density [18]. In Budapest, bike-sharing stations are strategically located to provide seamless integration with other forms of public transport, such as buses, trams and metro lines, allowing for a multimodal approach to urban mobility. The visualisation provided by the map demonstrates not only the city's commitment to fostering a bike-friendly environment but also the critical role of infrastructure placement in encouraging cycling as a viable transport option. This alignment of bike hubs with dense road networks supports the city's long-term goals of reducing traffic congestion and promoting healthier, more sustainable urban living.

3.5 The description statistics

The SP survey was distributed in Budapest, Hungary during the springtime of 2022. The used tools in distributing the survey were emails, Facebook, LinkedIn, WhatsApp and Instagram. The survey was sent to people supported by text and pictures to make the survey understandable. The obtained sample contains 306 respondents after filtering and removing the incomplete surveys. The participants recorded their sociodemographic and travel characteristics as shown in *Tables 3* to *6*.

Table 3 shows the composition of the sample based on gender. The sample contains around 56% males and 43% females. While a very small percentage did not declare their gender (i.e. others). *Table 4* presents the distribution of age across the sample. Most of the sample is youngsters of the age range 18 to 54 years old. *Figure 2* shows that around 4 percent are older than 54 years old.

Table 3 – Gender

Gender	Percentage
Male	56.56
Female	42.93
Others	0.51

Table 4 – Age

Age class	Percentage
18-24	43.7
25-54	52.7
55-64	3.08
>=65	0.51

Table 5 presents the income class of travellers. 29.31% of participants are classified as high income, 22.62% of participants are classified as middle income and 29.56% of participants are classified as low income. It is worth mentioning that 18.515 of the participants refused to declare their salaries.

Table 5 – Income

Income level	Percentage
High income	29.31
Middle income	22.62
Low income	29.56
No answers	18.51

Most of the participants in the SP survey are workers and students as shown in *Table 6*, 45.76% and 44.47%, respectively. The retired and the unemployed generally travel less than workers and students.

Table 6 – Job

Job status	Percentage
Workers	45.76
Unemployed	1.29
Student	44.47
Retired	5.66
Others	2.83

The education levels of participants are varied as shown in *Figure 3*. Around 10 percent of the participants have a high school degree as a higher education level. The majority of the participants are undergraduate or graduate students. This reflects the education level in the city and the reliability of answers.

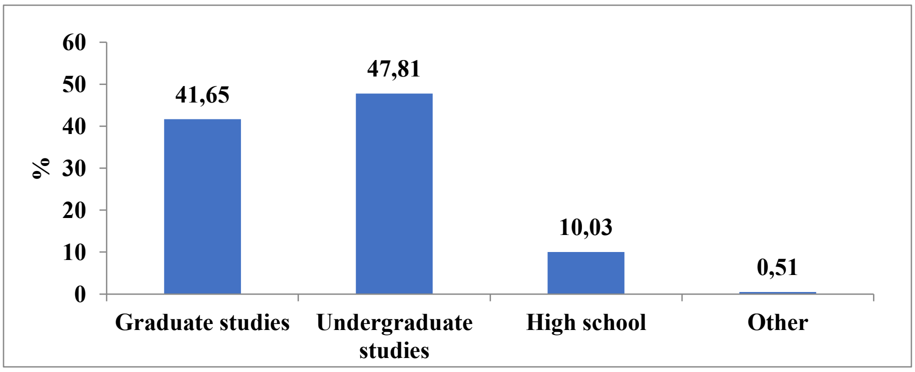

Figure 3 – Education

Travel characteristics of travellers are shown in *Figure 4* and *Table 7*. People declare their intention to use e-bikes and bikes when they are travelling on their most frequent trips in urban areas, as shown in *Figure 4*. Most travellers want to use e-bikes and bikes when they travel for leisure activities. A relatively large percentage of participants (20.31) want to use e-bikes and bikes for education and work activities. The least favourable destinations to use e-bikes and bikes are home and shopping.

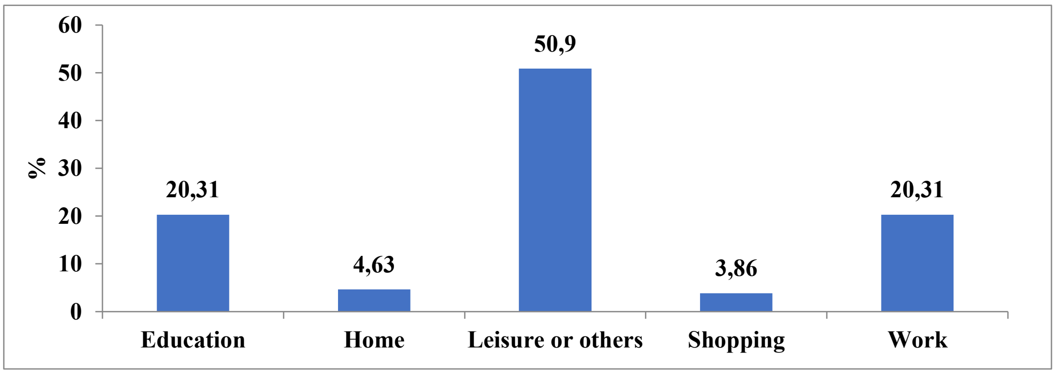

Figure 4 – Trip purpose

Table 7 presents the current frequent transport mode travellers use to reach their main destinations. It is shown that most of the participants use public transport mode and cars as drivers (i.e. 43.7% and 28.28%, respectively). 10.28% of the sample use cars as passengers, 3.08% of the participants use a taxi, 6.43% use micro-mobility and around 8% travel to their destinations on foot.

Table 7 – Transport mode

Transport mode	Percentage
Car as a driver	28.28
Car as passenger	10.28
Public transport	43.70
Personal bike/scooter	5.40
Shard bike/scooter	1.03
Taxi	3.08
Walking	7.97
Other	0.26

3.6 Model development

Two transport modes are studied in the developed model, the e-bike and bike. 306 travellers effectively participated in the SP survey, where their preferences toward the e-bike and bike are modelled using a multinomial probit model. A transport choice mode model is developed in which the variables and factors that impact choosing a transport mode are demonstrated. The factors that show significant results are kept in the model. The factors that have an impact on the selection of a transport mode at an acceptable significant level are kept in the model, such as walking time, trip time, trip cost, parking type, transport mode, education, trip purpose, gender, age and occupation, as shown in *Table 4*. The analysis tool that is used in the analysis is the Stata Software 16.1. The utility of factors in selecting a transport mode alternative is presented in *Table 4* and explained in the next chapter.

4. RESULTS

4.1 Model estimates

The multinomial probit choice model is developed where the fitting information of the model is presented in *Table 8*. The number of observations is 3,672 (306 travellers), the chi-square is 2558.35, the log simulated likelihood is -1129.583, and the model is significant (i.e. prob>chi square). This model is chosen over other models based on the Bayesian information criterion (BIC), where the lowest BIC a model gives is chosen [42]. The insignificant parameters at a confidence level of 95% are kept in the model for comparison.

Table 8 – The statistics of the model

The number of observations	Chi2(2)	Log simulated likelihood	Prob > chi2	AIC	BIC
3672	2558.35	-1129.583	0.0000	2315.167	2469.597

The estimates of the parameters are shown in *Table 9*. Trip cost, trip time, walking and parking demonstrate a negative impact on choosing a transport mode. The utility of travelling by bike or e-bike is associated with negative utilities, such as trip time is decreased by 0.049 per one unit increase in trip time (i.e. the unit of time is minute), trip cost is associated with -0.002 per one unit increase in trip cost (i.e. the unit of cost is Hungarian forint), and an increase one unit in walking time is associated with a decrease of utility by 0.065. The results of the model demonstrate that trip time and trip cost have a negative effect on the utility of travellers. Moreover, the parking type affects the choice of travellers as shown in *Table 9*. It is shown in the model that people are more willing to use bikes or e-bikes when the parking type is free floating. The probability of choosing a transport mode with parking lots is less than a transport mode with free-floating parking by 0.681. The parking lots are associated with low utility compared to free parking. In the developed model, the walking time represents the walking from and to parking points. The increase in walking time is associated with an increase in the negative utility of parking type.

Equation 5 is applied, where the willingness of travellers to pay for saving travel time is calculated. Trip time is represented by the walking time and actual trip time by e-bike/bike. The value of travel time (VOT) is 3,420 Hungarian forint per hour (8 euros). Compared to other studies, the VOT in our research is lower than it is in Germany with a VOT of 18.5 euro/hour and South Korea with a VOT of 16.02 euro/hour [29]. This could be explained by the fact that this study includes income and age categories to control individuals' socio-economic characteristics, which can reduce the coefficients of time if it is correlated with such variables. It is worth mentioning that the type of parking lot is always associated with walking distance because the bike or e-bike is a shared mode, and it depends on the available space for parking close to the destinations of travellers.

In *Table 9*, the reference transport mode (i.e. alternative) is an e-bike. The first column represents the variable, and the second column is the coefficient value (β). The third column represents the standard errors, the fourth and the fifth columns are the significance values, and the Exp(β) expresses the probability ratio. The significance of the variables is varied.

1) Transport mode

All transport modes show significant results at an acceptable confidence level ranging from 99% to 90% (e.g. the other class is not significant because it is a small group). The relative risk ratio for a traveller to switch from a car as a driver to a car as a passenger is 1.751, which means that the probability of a traveller who uses a car as a passenger to switch to a bike in his/her main trip purpose in urban areas is higher than who use the car as a driver. The probability of a traveller who uses public transport, personal bike or scooter, shared bike or scooter, taxi, walking and other to switch to bike in his/her main trip purpose in urban areas are 1.809, 1.978, 2.505, 2.328 and 1.598, respectively, higher than for those who use the car as a driver.

The relative risk ratio switching from the car as a driver to the car as a passenger for being on the bike is 1.751 (i.e. the probability of staying on the bike for travellers who use the car as a passenger is higher than those who use the car as a driver).

The results show that car as driver mode users do not prefer to use bikes compared to other transport modes.

2) Education

The relative risk ratios indicate that travellers with high school and undergraduate degrees are more likely to choose bikes compared to those with graduate degrees. Specifically, the probability of individuals with a high school education using bikes is 1.613 times higher than those with a graduate degree, while for those with an undergraduate degree, it is 1.424 times higher.

3) Trip purpose

The relative risk ratios indicate that individuals traveling for home, shopping, and leisure activities are more likely to use a bike compared to those traveling for educational purposes. Specifically, the likelihood of using a bike is 1.311 times higher for those traveling home, 1.142 times higher for those shopping, and 1.366 times higher for those engaging in leisure activities. However, individuals traveling for educational purposes are more likely to use bikes than those commuting for work, as the probability of bike use for work trips is lower, with a relative risk ratio of 0.842.

4) Gender

The relative risk ratio for male travellers using bikes compared to females is 0.853, indicating that males are less likely to use bikes than females. This suggests that female travellers have a higher likelihood of choosing bikes over other transport modes.

5) Age

The likelihood of choosing a bike increases with age. The relative risk ratio for individuals aged 25–54 compared to those aged 18–24 is 1.456, while for those aged 55–64, it is even higher at 2.212. This suggests that older individuals, particularly those between 25–64, are more likely to use bikes compared to younger individuals aged 18–24.

6) Occupation

The relative risk ratios indicate that individuals in specific job categories are less likely to use bikes compared to those in unspecified occupations. Workers, students, retirees, and unemployed individuals have lower probabilities of using bikes, with risk ratios of 0.453, 0.552, 0.712, and 0.337, respectively. However, among these groups, the unemployed have the highest likelihood of using bikes, followed by workers, students, and retirees.

The alternative specific constant (β0) is given to show the relative risk ratio of choosing a bike regardless of observed factors. The relative risk ratio of choosing a bike over an e-bike is -0.276. Thus, travellers' willingness to use e-bikes is more than conventional bikes.

Table 9 – Multinomial probit model estimates

Variable	Coefficient	St. errors	z	P>z	Exp(B)
Total trip time	-0.049	0.006	-7.82	0.000*	0.952
Total trip cost	-0.002	0.000	-9.21	0.000*	0.998
Walking time	-0.065	0.016	-4.01	0.000*	0.937
Parking type (lots)	-0.384	0.057	-6.72	0.000*	0.681
Transport mode					
Car as a driver	Base				
Car as passenger	0.560	0.301	1.86	0.063***	1.751
PT	0.593	0.233	2.55	0.011**	1.809
Personal bike or scooter	0.682	0.322	2.12	0.034**	1.978
Shared bike-scooter	0.918	0.210	4.38	0.000*	2.505
Taxi	0.845	0.493	1.72	0.086***	2.328
Walking	1.353	0.300	4.5	0.000*	3.868
Other	0.468	0.475	0.99	0.324	1.598
Education					
Graduate studies	Base				
High school	0.478	0.283	1.69	0.092***	1.613
Undergraduate studies	0.354	0.179	1.98	0.048**	1.424
Other	9.049	0.579	15.62	0.000*	8511.30

Variable	Coefficient	St. errors	z	P>z	Exp(B)
Trip Purpose					
Education	Base				
Home	0.271	0.399	1.77	0.077***	1.311
Work	-0.172	0.232	-2.04	0.041**	0.842
Shopping	0.133	0.354	0.97	0.338	1.142
Leisure or others	0.312	0.185	1.68	0.093***	1.366
Gender					
Female	Base				
Male	-0.159	0.162	-1.53	0.127	0.853
Others	-9.169	0.521	-17.6	0.000*	0.000
Age					
18-24					
25-54	0.376	0.202	1.86	0.062**	1.456
55-64	0.794	0.564	1.49	0.136	2.212
>=65	0.268	0.506	0.53	0.596	1.307
Occupation					
Other work types	Base				
Workers	-0.791	0.550	-1.94	0.051**	0.453
Student	-0.594	0.550	-1.88	0.060**	0.552
Retired	-0.340	0.652	-1.03	0.303	0.712
Unemployed	-1.088	0.993	-1.1	0.273	0.337
Constant (β0)	**-0.276**	**0.644**	**-0.43**	**0.668**	**0.759**

** p<0.01, ** p<0.05, *** p<0.1, the reference alternative is e-bike.*

4.2 Margins

The predictive margins are significant at a confidence level of 99%. The expected probability of choosing bikes is 41.28% and to choose e-bikes is 58.72%, as shown in *Figure 5*.

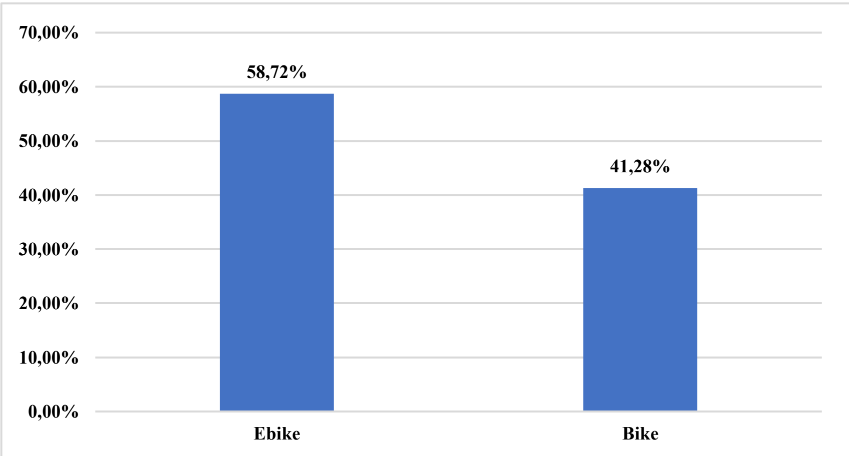

Figure 5 – Margins

The margins are changed across parking type variables as shown in *Figure 6*. The predicted margins show significant results at the confidence level of 95% with a standard error of less than 8%. The margins of e-bikes and bikes when travellers use free-floating parking are 63.39% and 42.25%, respectively. The margins of e-bikes and bikes when travellers use the parking lot are 53.49% and 36.37%, respectively. The margin is based on changing the variables of the transport mode. For example, when the parking type is free-floating on the e-bike, the parking type on the bike is parking lots.

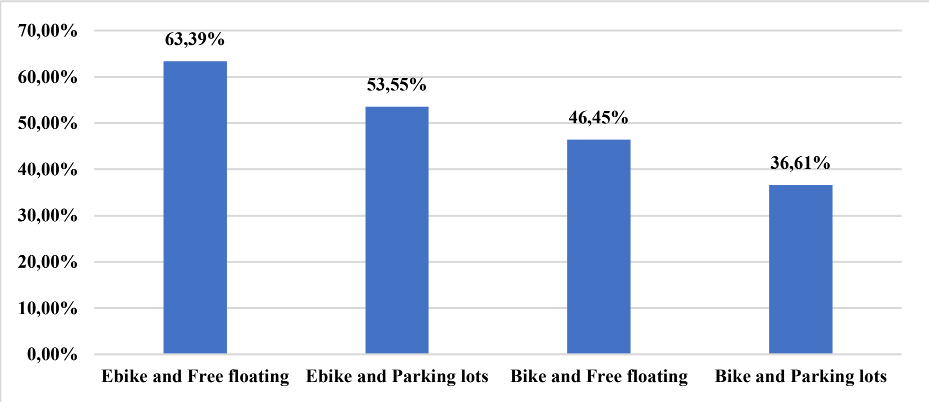

Figure 6 – Margins across parking type

The margins show that both bikes and e-bikes have the largest margin across free floating as shown in *Table 10*. It is also shown that the margins are changed across alternative parking types, for example, the margin is 63.50% for e-bike when the parking type of bike is parking lots.

Table 10 – Predictive margins

Outcome, alternative of parking type	Margin	Std. err.	z	P>z
E-bike, e-bike and free floating	63.39%	0.0739809	8.57	0.000
E-bike, e-bike in parking lots	53.55%	0.0766118	6.98	0.000
E-bike, bike has free floating	53.55%	0.0765984	7.02	0.000
E-bike, bike in parking lots	63.50%	0.0739045	8.61	0.000
Bike, bike and free floating	36.50%	0.0739809	4.95	0.000
Bike, bike in parking lots	46.45%	0.0766118	6.07	0.000
Bike, e-bike and free floating	46.45%	0.0765984	6.04	0.000
Bike, e-bike and parking lots	36.61%	0.0739045	4.92	0.000

Table 10 presents the predictive margins of choosing either an e-bike or a bike under different parking scenarios (free-floating or parking lots). The margins represent the probability of selecting a transport mode given the specified parking type for both options.

— Free-floating parking increases the likelihood of choosing an e-bike or bike. The highest predicted margin is 63.39% when both the chosen and alternative transport modes are e-bikes with free-floating parking. Similarly, when a bike is the chosen mode, its margin is 36.50% under the same condition.
— Using a parking lot reduces the likelihood of choosing either transport mode. When both the chosen and alternative transport modes require parking lots, the probability of choosing an e-bike drops to 53.55%, and for a bike, it drops to 46.45%. This indicates that users prefer free-floating parking over fixed parking facilities.
— Alternative parking type also influences preferences. For example, when an e-bike is the chosen mode and the alternative mode is a bike with parking lots, the probability of choosing the e-bike reaches 63.50%. This suggests that when a bike is restricted to a parking lot, users are more inclined to opt for an e-bike.

— Comparison between e-bike and bike: The results indicate that, in all scenarios, the likelihood of choosing an e-bike is consistently higher than that of a bike, reinforcing the preference for e-bikes over regular bikes in shared mobility systems.

The margins are predicted based on the changes in the attributes of each transport mode. Mainly, the parking type, which is the concern of most travellers, is highlighted in this study. It is worth mentioning that free-floating parking needs extra work from operators, such as charging the bikes and redistributing them.

5. DISCUSSION

5.1 Comparison with other studies

This study provides insight into people's preferences for micro-mobility in the form of electric bikes (e-bikes) and regular bikes, focusing on short trips in urban areas, specifically in Budapest, Hungary. Using a multinomial probit model, the study identified key factors influencing transport mode choices, such as trip cost, trip time, walking distance and parking type. Our results align with previous research in several ways but also highlight some unique findings that contribute to the growing body of literature on micro-mobility.

Several studies have emphasised the importance of parking type, which is consistent with our finding that free-floating parking significantly increases the likelihood of e-bike usage over regular bikes. For instance, Bai and Jiao (2020) [25] explored the impact of parking availability and its role in encouraging the adoption of micro-mobility services, noting that flexible parking solutions are critical for increasing micro-mobility usage. Similarly, Reck et al. (2022) [19] found that free-floating parking systems led to higher user satisfaction and increased adoption of shared e-scooters, which aligns with our findings regarding e-bikes.

Our results also demonstrated a strong preference for e-bikes over regular bikes, especially when trip time and walking distance were reduced. This supports the findings of studies by Hatami et al. (2023) [27] and Zhao et al. (2020) [23], which showed that travellers are more likely to opt for modes of transport that minimise travel and walking times. Specifically, our study aligns with Rayaprolu and Venigalla (2020) [20], who highlighted that users of micro-mobility devices, such as e-bikes, prioritise convenience and time savings.

In terms of sociodemographic factors, our study found that younger, highly educated males are more likely to choose e-bikes over regular bikes, which is consistent with Reck and Axhausen's (2021) [21] findings on micro-mobility use in Zurich. Their study highlighted that young professionals, especially males, are early adopters of shared micro-mobility services, reflecting similar patterns in our Budapest case study. However, contrary to our findings, their study emphasised that income had a more significant effect on micro-mobility use than education level, suggesting that the influence of sociodemographic factors may vary across cities.

In terms of trip purpose, our study found that leisure trips and shopping are the most common activities for which travellers prefer using e-bikes or regular bikes. This aligns with research by Campisi et al. (2020) [22], who noted that micro-mobility is primarily adopted for non-work-related purposes, such as leisure or recreational trips. Our findings diverge slightly from Zhao et al. (2020) [23], who reported that public transport and micro-mobility users are more likely to use these modes for work-related trips.

5.2 Limitations and future research

While this study provides valuable insights, it has several limitations. First, the research focuses exclusively on Budapest, Hungary, which limits the generalisability of the results to other cities with different infrastructure, cultural habits or weather conditions. Future studies could replicate this research in different geographical contexts to determine if the observed patterns hold across various urban settings.

Second, the study only examines short urban trips, leaving the preferences for longer journeys unexplored. Future research should expand the scope to include longer commutes or intercity trips, where factors such as the availability of charging stations for e-bikes may play a more critical role.

Lastly, the study relies on stated preference data, which may not fully capture real-world behaviour. While discrete choice models are a powerful tool for analysing preferences, future studies could complement this approach with revealed preference data to ensure that the results accurately reflect actual transport mode choices. Moreover, additional factors such as safety concerns, environmental consciousness and the availability of infrastructure (e.g. dedicated bike lanes) should be incorporated into future models.

5.3 Policy implications

The study demonstrates that using either bikes or e-bikes in travelling is highly impacted by the parking type. From the result of this study, it is shown that free floating parking is more preferable to people than parking lots. The connected attribute to parking type is walking time; free-floating parking minimises walking time. Minimising walking time impacts positively on the utility of travel. This introduces relevant policies that shape the use of free-floating parking. Planning, design, implementation and operating free-floating parking are factors that need to be considered in the road network design to encourage the eco-friendly modes. Placement, spacing, security, smart use, availability of shelters, type of bike, pricing, facility design inside the operating zone, insurance, security and regulations for operators and users are all variables to be considered to attract more bikers. The policy is effective when the design of urban streets includes spaces for bikes to be parked in a similar way to street car parking with compliance to standards, local regulation and laws.

6. CONCLUSION

This study provides a comprehensive analysis of urban travellers' preferences for e-bikes and regular bikes in Budapest. Trip time, trip cost, walking distance and parking type are used as parameters in a discrete choice modelling approach. These parameters are chosen because they significantly influence transport mode choice. The results reveal a clear preference for e-bikes over regular bikes, with free-floating parking being particularly favourable. These findings highlight the importance of flexible and convenient parking solutions in promoting the use of eco-friendly transport modes. The study also underscores the influence of sociodemographic variables, such as age, gender, education and employment status, in shaping transport mode preferences. Younger, educated males, in particular, showed a higher inclination towards e-bikes. This suggests that targeted policies and infrastructure improvements could further encourage the adoption of sustainable transport options among different demographic groups.

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REFERENCES

[1] Jaber A, Csonka B. Temporal travel demand analysis of irregular bike-sharing users. In: *HCI in Mobility, Transport, and Automotive Systems*. Springer; 2022. p. 517-525.

[2] Lierop Dv, Badami MG, El-Geneidy AM. What influences satisfaction and loyalty in public transport? A review of the literature. *Transport Reviews*. 2017. DOI: 10.1080/01441647.2017.1298683.

[3] Hamadneh J, Jaber A. Modeling of intra-city transport choice behaviour in Budapest, Hungary. *J Urban Mobil*. 2023;3:100049. DOI: 10.1016/j.urbmob.2023.100049.

[4] Guevara CA. Mode-valued differences of in-vehicle travel time savings. *Transportation*. 2017;44:977-997. DOI: 10.1007/s11116-016-9689-3.

[5] Beil D, et al. Modal shift measures to increase the use of eco-friendly transport modes: a literature review. *Transport Pro*. 2023;72:4279-4286. DOI: 10.1016/j.trpro.2023.11.343.

[6] Krisdiyanto A, et al. Challenges and solutions in developing eco-friendly electric vehicles with extended range. *WSIS Journal*. 2023;1:799-807. DOI: 10.58812/wsis.v1i09.232.

[7] Hamadneh J, et al. Stakeholder viewpoints analysis of the autonomous vehicle industry by using multi-actors multi-criteria analysis. *Transport Policy*. 2022;126:65-84. DOI: 10.1016/j.tranpol.2022.07.005.

[8] Ács A, et al. The future of sustainable mobility in Budapest in 2030. *Sustainable Mobility Studies*. 2023:37-56. DOI: 10.29180/9786156342560_3.

[9] Földes D, Přibyl O. Competitive or complementary? Analyzing bike-sharing use between public transport stops: A case study in Budapest. In: *2023 Smart City Symposium Prague (SCSP)*. IEEE; 2023. DOI: 10.1109/SCSP58044.2023.10146210.

[10] Weicker T, Tóth K. "I love Budapest. I bike Budapest?" Urban bicycle traffic in the Hungarian capital, 1980–2014. *SAGE Publ Sage UK: London, England*; 2021.

[11] Olabi AG, et al. Micromobility: Progress, benefits, challenges, policy and regulations, energy sources and storage, and its role in achieving sustainable development goals. *Int J Thermofluids*. 2023;17:100292. DOI: 10.1016/j.ijft.2023.100292.

[12] Jaber A, Csonka B. Towards a sustainable and safe future: Mapping bike accidents in urbanized context. *Safety*. 2023;9(3):60. DOI: 10.3390/safety9030060.

[13] Cornet Y, et al. Worthwhile travel time: A conceptual framework of the perceived value of enjoyment, productivity and fitness while travelling. *Transport Reviews*. 2022;42:580-603. DOI: 10.1080/01441647.2021.1983067.

[14] Hamadneh J, Esztergár-Kiss D. The effects of multitasking and tools carried by travelers onboard on the perceived trip time. *J Adv Transp*. 2021;25. DOI: 10.1155/2021/5597694.

[15] Small KA. Valuation of travel time. *Econ Transp*. 2012;1(1-2):2-14. DOI: 10.1016/j.ecotra.2012.09.002.

[16] Hamadneh JMJ. The implications of integrating autonomous vehicles into the transport system [dissertation]. Budapest: Budapest University of Technology and Economics; 2022.

[17] Hamadneh J, Esztergár-Kiss D. The preference of onboard activities in a new age of automated driving. *Eur Transp Res Rev*. 2022;14(1):15. DOI: 10.1186/s12544-022-00540-7.

[18] Reck DJ, et al. Explaining shared micromobility usage, competition and mode choice by modelling empirical data from Zurich, Switzerland. *Transp Res Part C Emerg Technol*. 2021;124:102947. DOI: 10.1016/j.trc.2020.102947.

[19] Reck DJ, Martin H, Axhausen KW. Mode choice, substitution patterns and environmental impacts of shared and personal micro-mobility. *Transp Res Part D Transp Environ*. 2022;102:103134. DOI: 10.1016/j.trd.2021.103134.

[20] Rayaprolu S, Venigalla M. Motivations and mode-choice behavior of micromobility users in Washington, DC. *J Mod Mobil Syst*. 2020;1. DOI: 10.13021/jmms.2020.2894.

[21] Reck DJ, Axhausen KW. Who uses shared micro-mobility services? Empirical evidence from Zurich, Switzerland. *Transp Res Part D Transp Environ*. 2021;94:102803. DOI: 10.1016/j.trd.2021.102803.

[22] Campisi T, Akgün N, Tesoriere G. An ordered logit model for predicting the willingness of renting micro-mobility in urban shared streets: A case study in Palermo, Italy. In: *Advances in Transport Systems and Technologies*. Springer; 2020. DOI: 10.1007/978-3-030-58802-1_57.

[23] Zhao X, et al. Prediction and behavioral analysis of travel mode choice: A comparison of machine learning and logit models. *Travel Behav Soc*. 2020;20:22-35. DOI: 10.1016/j.tbs.2020.02.003.

[24] Kutela B, et al. Analysis of residents' stated preferences of shared micro-mobility devices using regression-text mining approach. *Transp Plan Technol*. 2022;45(2):159-178. DOI: 10.1080/03081060.2022.2089145.

[25] Bai S, Jiao J. Dockless e-scooter usage patterns and urban built environments: A comparison study of Austin, TX, and Minneapolis, MN. *Travel Behav Soc*. 2020;20:264-272. DOI: 10.1016/j.tbs.2020.04.005.

[26] Caspi O, Smart MJ, Noland RB. Spatial associations of dockless shared e-scooter usage. *Transp Res Part D Transp Environ*. 2020;86:102396. DOI: 10.1016/j.trd.2020.102396.

[27] Hatami F, et al. Non-linear associations between the urban built environment and commuting modal split: A random forest approach and SHAP evaluation. *IEEE Access*. 2023;11:12649-12662. DOI: 10.1109/ACCESS.2023.3241627.

[28] Elhenawy M, et al. A novel crowdsourcing model for micro-mobility ride-sharing systems. *Sensors*. 2021;21(14):4636. DOI: 10.3390/s21144636.

[29] Jaber A, Hamadneh J, Csonka B. The preferences of shared micro-mobility users in urban areas. *IEEE Access*. 2023;11:74458-74472. DOI: 10.1109/ACCESS.2023.3297083.

[30] Hauber AB, et al. Statistical methods for the analysis of discrete choice experiments: A report of the ISPOR conjoint analysis good research practices task force. *Value Health*. 2016;19(4):300-315. DOI: 10.1016/j.jval.2016.04.004.

[31] Mangham LJ, Hanson K, McPake B. How to do (or not to do)... Designing a discrete choice experiment for application in a low-income country. *Health Policy Plan*. 2009;24(2):151-158. DOI: 10.1093/heapol/czn047.

[32] Lancsar E, Louviere J. Conducting discrete choice experiments to inform healthcare decision making. *Pharmacoeconomics*. 2008;26(8):661-677. DOI: 10.2165/00019053-200826080-00004.

[33] Rose JM, Bliemer MCJ. Constructing efficient stated choice experimental designs. *Transp Rev*. 2009;29(5):587-617.

[34] Johnson FR, et al. Constructing experimental designs for discrete-choice experiments: Report of the ISPOR conjoint analysis experimental design good research practices task force. *Value Health*. 2013;16(1):3-13.

[35] de Bekker-Grob E, et al. Sample size requirements for discrete-choice experiments in healthcare: A practical guide. *Patient Cent Outcomes Res*. 2015;8:373-384.

[36] Schmitz C. LimeSurvey: An open-source survey tool. *LimeSurvey Project Hamburg, Germany*; 2012. Available from: http://www.limesurvey.org.

[37] Cascetta E. Random utility theory. In: *Transportation Systems Analysis*. Springer; 2009. p. 89-167.

[38] Hensher DA, Greene WH. The mixed logit model: The state of practice. *Transportation*. 2003;30:133-176.

[39] Polydoropoulou A, et al. Who is willing to share their AV? Insights about gender differences among seven countries. *Sustainability*. 2021;13(9):4769. DOI: 10.3390/su13094769.

[40] Hamadneh J, Esztergár-Kiss D. The preference of onboard activities in a new age of automated driving. *Eur Transp Res Rev*. 2022;14(1):15. DOI: 10.1186/s12544-022-00540-7.

[41] Jaber A, Csonka B. Assessment of Hungarian large cities' readiness in adopting electric bike-sharing systems. *Discov Sustain*. 2024;5(203). DOI: 10.1007/s43621-024-00413-0.

[42] Jaber A, Csonka B. Investigating the temporal differences among bike-sharing users through comparative analysis based on count, time series, and data mining models. *Alex Eng J*. 2023;77:1-13. DOI: 10.1016/j.aej.2023.06.087.