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Analysis of attitudes and engagement of shared e-scooter users

Abstract

Micromobility and especially e-scooter sharing have recently attracted a lot of attention, due to the rapid spreading of e-scooters in many cities around the world. However, many local authorities have not yet been prepared for efficiently integrating e-scooters in their transport systems and the exact impact of e-scooters is still unclear. It is therefore essential to understand the way e-scooters operate and their users' profile. To address these questions, a study was designed based on 578 questionnaires (271 by e-scooter users and 307 by non-users) in the city of Thessaloniki, Greece. The analysis utilized a classification tree model for identifying the characteristics of people that are attracted by e-scooters (i.e., used them more than once) and a latent variable logit model for understanding the attributes of the regular e-scooter users. The results show that shared e-scooters mostly replaced walking and public transport trips; therefore, the positive impact of e-scooters on the environment is questioned. Also, the results indicate that people traveling with bicycle or motorcycle were not at all attracted by e-scooters. Moreover, females seem to be less keen on using e-scooters compared to males, while people living downtown are more regular users compared with those living in longer distances from the city center. These findings can aid policymakers in shaping the manner with which e-scooters can be incorporated in their cities.

Keywords: e-scooter, micromobility, sustainable urban mobility, user profile

1. Introduction

Urban areas are continuously expanding, and current projections indicate that in the future most people will be urban dwellers (United Nations, 2019). Reliance on automobile to fulfill mobility needs has resulted in increased congestion and associated pollutants while public transportation is not capable of addressing increased urban mobility demand (Zarif, Pankratz and Kelman, 2019). For this reason, several new mobility concepts have emerged. One of these concepts is shared mobility, which is a fast-growing sector of the transportation-sharing economy and includes several services, such as car-sharing and bike-sharing (Shaheen et al., 2017). A more recent service that belongs to the shared mobility sector is the shared electric scooter (e-scooter), which is constantly expanding around the world (Shaheen, et al., 2020). E-scooters have experienced a tremendous rise globally and they are currently widely used in several countries (Lee et al., 2019; Tuncer et al., 2020).

Recent data from operations in U.S. cities and in Paris, France showed that e-scooters have aided in reducing automobile use and gas emissions as well as increasing mobility (Shaheen and Cohen, 2019; Lime, 2019). E-scooters can also provide extended coverage of urban residents' mobility needs especially in areas with limited or infrequent transit service (Zarif, Pankratz and Kelman, 2019). E-scooters seem to have surpassed the utility of shared bicycle programs (Hardt and Bogenberger, 2019) and they seem to control the micromobility market globally. Nevertheless, their wide use has generated issues regarding their inappropriate use on sidewalks and parking at improper areas, such as on sidewalks and at spots that block pedestrian movement (Raptopoulou et al., 2020), as well as regarding the environment, such as the mass e-scooter garbage dumps (Zagorskas and Burinskiene, 2019). Significant concerns regarding riders' safety have emerged, since a growing trend for crashes involving e-scooters has been observed, and recent studies have revealed these issues using either questionnaires (Comer et al., 2020) or mobile sensing and news reports data (Yang et al., 2020; Ma et al., 2021). In some cases, e-scooter companies do not sufficiently promote content regarding safety aspects, which could increase the awareness of safety issues for users (Dormanesh, Majmundar and Allem, 2020).

To address these issues, cities are developing guidelines and policies that could reduce these problems through developing proper frameworks for their operation that include acceptable operating speeds, helmet requirements, minimum age for use, permitted operation locations and organized parking areas despite their dock-less nature (Gössling, 2020; de Bortoli and Christoforou, 2020). However, it seems that the majority of local authorities have not yet prepared the necessary regulations for efficiently integrating e-scooters in the urban context (Chang et al., 2019).

A critical aspect of understanding the impact of these systems and developing policies to tackle their various operational and safety problems is the identification of the user profile. Some efforts have been undertaken in the U.S. to understand who uses shared e-scooters. Populus (2018) noted that the percentage of women using shared e-scooters is very close to the respective percentage of men resulting in bridging existing gender mobility gaps. On the other hand, other studies showed that men are much more likely than women to ride a shared e-scooter (Denver Public Works, 2019; San Francisco Municipal Transportation Agency, 2019). The study of the San Francisco Municipal Transportation Agency (2019) also identified that most of the users belong in the 25-34 age group, as well as that most of them would have used a ride-hailing service if a shared e-scooter was not available. The fact that shared e-scooters mainly attract young people under the age of 40 was also noted in other studies (Baltimore City Department of Transportation, 2019; City of Santa Monica, 2019). Caspi, Smart and Noland (2020) used data from the companies operating in Austin, Texas and they identified that students comprise a large proportion of all e-scooter trips. Sanders, Branion-Calles and Nelson (2020) focused their analysis in the city of Tempe, Arizona and pointed out that race/ethnicity has also an impact on intention to use e-scooters.

Caspi, Smart and Noland (2020) also concluded that most e-scooter trips are being carried out in areas with sufficient bicycle infrastructure and in areas with high employment rates as well as that commuting is not the most frequent trip purpose among e-scooter users. Similarly, a Calgary, Canada survey with 7,671 respondents identified that the vast majority of e-scooter trips are for recreation or social gatherings, and that approximately half of these trips would have been carried out on foot if a scooter was not available (City of Calgary, 2020). Another study that used data from Washington, D.C., compared usage patterns for bike-sharing and e-scooter sharing services and determined that bike-sharing is mainly used for trips to/from the work, while e-scooters for other trip purposes (McKenzie, 2019). Zhu et al. (2020) conducted a similar study in Singapore and confirmed that the operation of e-scooter sharing systems has important differences when compared with the operation of bike-sharing systems. In contrast with conclusions that presented above, Sanders, Branion-Calles and Nelson (2020) concluded that e-scooters are used more for mandatory trip purposes rather than for recreation. A study in Portland, Oregon identified that e-scooters have attracted new people in active transportation and most of the users replaced driving and ride-hailing trips (Portland Bureau of Transportation, 2018).

Of interest are also the results of studies that utilize rental data of e-scooter use and apply spatial analyses. Hosseinzadeh et al. (2020) explored the use of e-scooters in Louisville, Kentucky and concluded that areas with increased walkability and bikeability are preferred by e-scooter riders, indicating that all active and micromobility modes are favored by similar built environment characteristics. Based on data from Austin, Texas, Jiao and Bai (2020) identify that e-scooter usage hotspots are in the downtown and at the University of Texas campus, both areas with high population and activity densities. Moreover, they emphasized that greater population density results in higher e-scooter usage. Zou et al. (2020) analyzed data from Washington, D.C. and examined the use of e-scooters not at the area level, but at a street level. Their analysis showed that streets equipped with bike lanes attract greater e-scooter traffic.

Current understanding of the e-scooter usage is based mostly on studies completed in U.S. cities. However, it is not clear if the differences in the residential density, trip lengths and public transport characteristics that can be observed between North American and European cities (Milakis, Vlastos and Barbopoulos, 2008) could also result in differences of e-scooter usage between Europe and North America. The relevant literature from European countries is still in its nascent stages. Laa and Leth (2020) have completed one of the few such attempts utilizing 166 e-scooter users' questionnaires and field observations in Vienna, Austria. Their results show that most users are young, male and they have a high level of education. Moreover, they identify that e-scooter trips mostly replaced walking and public transport trips. The replacement of walking and public transport was also a conclusion of the Sellaouti, Arslan and Hoffmann (2020) study, which was based on 277 questionnaires gathered in Munich, Germany.

This study aims to advance and expand understanding of the shared e-scooter users' profile and provide insight on their attitudes and behavior, as well as on factors that can further promote and facilitate the use of e-scooters as a transportation mode. The study surveyed both users and non-users in Thessaloniki, Greece, offering the possibility for a more holistic identification of society's attitudes. Thessaloniki is a case of great interest, since there are only limited and descriptive attempts for identifying e-scooter users' profile in European cities, while it is also considered as a place where e-scooters met a great success, despite the fact that other alternative mobility options (e.g., bicycles) are not at all popular. Furthermore, this study investigates the profile of e-scooter users through an in-depth statistical analysis with appropriate and robust modelling techniques. The results from this study are compared with outcomes from other similar studies, in an attempt to synthesize these findings and provide strong evidence about who are the shared e-scooters users. This would allow for setting the foundation of understanding the impact of e-scooters in modern transportation systems.

2. Description of the undertaken research

2.1. Study area

Thessaloniki is located in Northern Greece and it is the second largest city in Greece with a population of approximately 1.1 million residents according to the 2011 census. The city boasts a major commercial port, is a popular tourist destination, and attracts a large number of students because of the existence of many Universities. The geography of the city is relatively flat, with some exceptions in neighborhoods that are located in the northern part of the city. For many years, the transport policy and practice in the city was car-oriented, while the quality of public transport services in the city is rather poor (as it is perceived by the users in Vaitsis, Basbas and Nikiforiadis, 2019), since only public buses are available and a metro system is under construction for approximately 15 years. However, public transport is preferred by a large proportion of Thessaloniki's citizens due to its extended coverage, the unavailability of a private vehicle and the low fares (Papagiannakis, Baraklianos and Spyridonidou (2018) identified a correlation between household income and public transport usage).

Thessaloniki is also a city with very low cycling volumes (Nikiforiadis, Basbas and Garyfalou, 2020) and this is to a large extent attributed to the limited and fragmented cycling network (Stamatiadis et al., 2020). More specifically, the bicycle network in the city is 12km in total, while an additional temporary segment of 3km was recently implemented in response to the COVID-19 pandemic. There is congestion along the main arterials especially during peak-hours (between 15:00 and 19:00) and a modal share which favors private cars (41.3%) with a high share of public transport (33.7%) and motorcycles (11%) (Thessaloniki SUMP, 2019). On the contrary, non-motorized modes claim a low transport mode share with 9.2% walking and 1.7% cycling trips (Thessaloniki SUMP, 2019).

Also, a dock-based bike-sharing system operates in Thessaloniki since 2013. However, its limited number of stations does not provide sufficient access in many areas of the city;

therefore, it has attracted only a limited number of users and mostly for recreational trips along the city's waterfront (Boufidis et al., 2020). Recently, a dock-less bike-sharing system started its operation in the city. It should be noted that other forms of sharing services (e.g., car-sharing) are not currently available in Thessaloniki.

The first e-scooter sharing company arrived in Thessaloniki in the end of 2018. Despite the fact that alternative modes of transport (e.g., cycling) were not popular in the city and citizens had limited familiarization with sharing services, e-scooters became rapidly a trend. After one year of operation, Lime (the first company to operate in the city) had served approximately 850,000 trips in Thessaloniki. The great success of Lime led to the introduction of more e-scooters and to the attraction of two more companies (Hive and Rise). This success is also of great interest considering the cost of using shared e-scooters (3.25€ for a 15-minute average trip in Thessaloniki), which is much higher than the cost of public transport (0.90€ for a regular ticket and 0.45€ for a discounted one).

The sprawl of e-scooters within the city provoked a great debate about the pros and cons of the new service, as well as intensified views on the need for measures and regulatory framework. One of the most immediate measures was the application of a 20km/h speed limit. However, a framework did not exist in Greece when they were introduced. The recently established regulatory framework equates e-scooters with bicycles and therefore it states that they should be used on roads (as bicycles are required to do) and not on roads where the speed limit is over 50km/h. Moreover, the regulatory framework mentions the necessary equipment for the vehicles and the riders (e.g. lights, helmets), but it does not specify restrictions for e-scooters parking. Finally, it should be noted that over time the strong trend of using e-scooters has been moderated and Hive has already stopped operations. However, e-scooters retain a reasonable transport market share in Thessaloniki.

2.2. Data collection and analysis approach

The current research aims to document the attitudes and behaviors of e-scooter users, as well as the attitudes of non-users. Most importantly, it aims to identify the profile of people that were attracted to e-scooters (for this study, people that have used e-scooters more than once were considered as attracted) and the profile of people that were engaged in the use of e-scooters (i.e., those that used them regularly as it was revealed by a set of questions that show the usage frequency for different trip purposes). Figure 1 presents the data collection and analysis approach that was followed for achieving the study objectives.

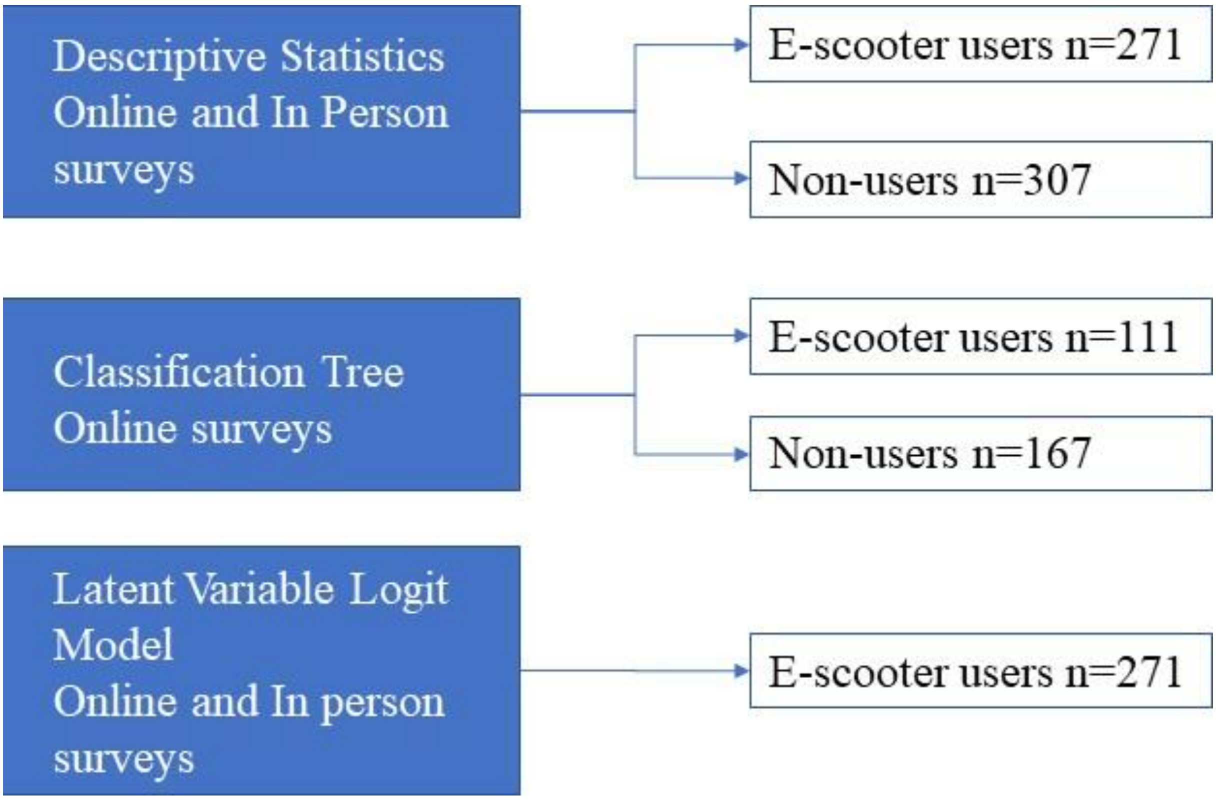

Figure 1: Types of analysis used and their data sources

The necessary data for the completion of the analysis were collected through two questionnaires (one targeting the users and a second the non-users) that were administered both face-to-face and electronically. The team reviewed pertinent literature in determining the questionnaire questions. For users, the information collected included the respondents' demographic characteristics, the frequency of use, the duration and purpose of trips, the transport mode that they mostly use when an e-scooter is not available, and factors that would affect the frequency of use. For non-users, the information collected included the respondents' demographic characteristics, their most common means of transport, perceived situations of e-scooters affecting safety and comfort of both pedestrians and vehicles, factors preventing them from using e-scooters, and their opinion on certain interventions that will improve e-scooter use. It should be noted that the electronic forms of the questionnaires had some additional questions about the respondents' occupation, education level and place of residence, which were not included in the face-to-face questionnaire in order to keep it brief and discreet.

A pilot study was undertaken after the initial development of the questionnaires which allowed the team to address any points that could lead to misinterpretation of the questions and require additional clarification. The final dissemination took place during the July-October 2019 period with most of the interviews were conducted in the afternoon and evening. The electronic questionnaire was posted on a website and data were collected in October 2019. For the e-scooter users, a total of 160 surveys were completed in person and 111 online. For the non-users, 140 were in-person surveys and 167 online. Thus, the totals were 271 user and 307 non-user surveys. The distribution of the online survey participants per Municipality in the city of Thessaloniki is presented in Figure 2.

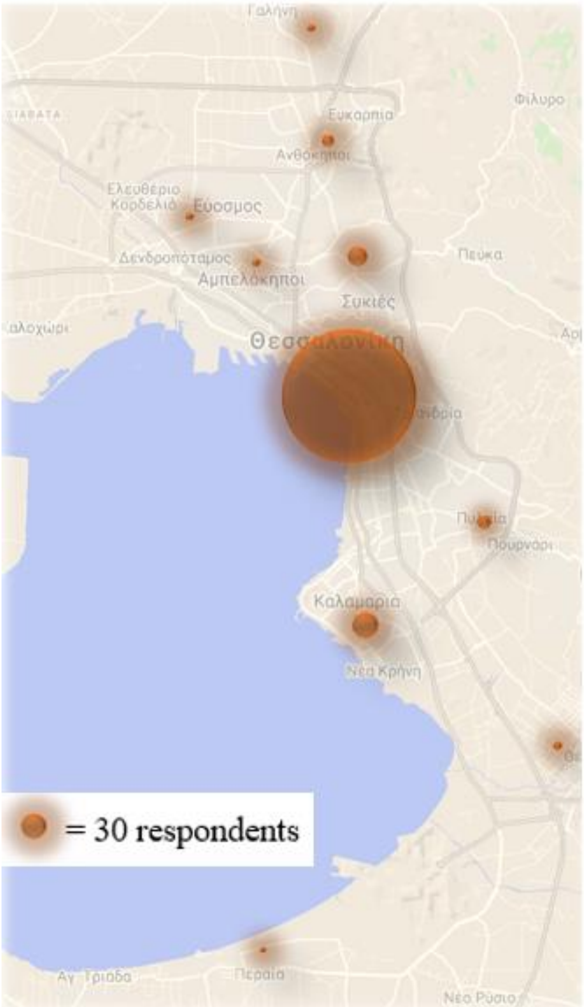

Figure 2: Distribution of the online survey participants per Municipality (Cartographic background: Google, n.d.)

The first analysis step was to conduct a descriptive examination of the responses for understanding users' behavior and attitudes, as well as the opinions of non-users. A classification tree approach was used next to investigate the characteristics of those that were attracted by e-scooters. The specific supervised machine learning approach, which belongs to the decision trees family, was considered appropriate for this part of the analysis due to several reasons. Decision trees are probably one of the most commonly and successfully applied techniques for market (e.g., users or customers) segmentation (Abad-Grau, Tajtáková and

Arias-Aranda, 2009; Tirenni, Kaiser and Herrmann, 2007). The popularity of this approach for market segmentation is attributed to the fact that it is one of the most “white-box” machine learning algorithms (i.e., the outcome is transparent and the interpretation clear) as well as to the ease interpretation they provide due to their graphical display and their “if-else” form (James et al., 2013). An additional reason for using decision trees is that they are nonparametric and nonlinear, thus they do not require assumptions about distribution and linearity, and at the same time they provide satisfactory accuracy. Moreover, typical disadvantages of decision trees, i.e., instability and overfitting, did not affect this analysis due to the application of a tree pruning technique, while the stability of the results was confirmed by the common structure of the tree in all examined cases of training-test set separation. In this study, three training-test set separations were examined (60%-40%, 70%-30%, and 80%-20%).

For the classification tree analysis only the responses that were gathered through the web-based survey (n=278) were utilized in order to allow for a randomly selected sample from the total population of the city of Thessaloniki. It was assumed that the web-based survey was equally accessible to both e-scooter users and non-users. The common variables in both questionnaires were examined as potential independent variables in the model and included respondents’ personal characteristics (i.e., gender, age), socioeconomic characteristics (i.e., education, income, occupation, area of residence), mobility characteristics (i.e., most commonly used transport mode, ownership of private car).

The last step of the analysis is the investigation of the characteristics of those that became frequent e-scooter users (i.e., became engaged in the use of e-scooters) and they did not just used them out of curiosity. This analysis was based only on the users’ sample (n=271) and it was approximated via a model based on a latent variable framework. In particular, participants’ responses related to the frequency of use, with respect to the various trip purposes, were assumed of consisting underlying indicators of engagement where higher engagement of an individual results in higher frequency of use. The level of engagement is affected by factors which were considered in the form of explanatory variables and explained at a later section.

3. Results

3.1. Descriptive statistics

3.1.1. E-scooter users

This section provides an overview of the characteristics of the e-scooter users' sample, and reveals aspects that are associated with their attitudes and behavior. Most respondents (68.6%, 186) are males and 73.4% (199) belong in the 18-27 age group (it is noted that only adults were permitted to participate in the survey). The age distribution is to a large extent right-skewed, since only 7 respondents (2.6%) had an age over 54 years. The distribution of the respondents' annual income is approximately normally distributed where 28.4% (77) indicated income in the 12,000-24,000 €/year and with sufficient sample sizes in all other income classes. A large portion of the respondents (19.6%) preferred to not answer this question.

Table 1 summarizes the responses of e-scooter users regarding behavioral aspects and more specifically with the e-scooter usage frequency either alone or in combination with another transport mode and the transport mode that they select when they cannot use an e-scooter. The data in Table 1 indicate that multimodal trips, including e-scooter for a part of the trip, are very rare and only a few of the respondents engage in such trips. E-scooters attracted a large proportion of trips that in another case would be mainly made on foot and possibly with public transport. On the other hand, the shift from private vehicles to e-scooters is rare. The data also indicates that e-scooters have not yet become a commuting option and they are mostly seen as a mean for leisure trips.

Table 1: E-scooter users' behavior responses

Description	Responses	Distribution
Frequency of using e-scooter in combination with another transport mode	more than 1 time per day	1.5%
	1 time per day	2.6%
	3-6 times per week	3%
	1-3 times per week	16.6%
	less than 1 time per week	55.7%
	never	20.7%
Transport mode choice when e-scooter is not available	on foot	43.9%
	bicycle	6.6%
	car or motorcycle	13.3%
	public transport	32.8%
	taxi	3.3%
Frequency of using e-scooter for work purposes	daily	1.8%
	more than 4 times per week	3%
	2-4 times per week	2.6%
	1 time per week	5.2%
	1-5 times per month	10%
	less than once per month	11.1%
	never	66.4%
Frequency of using e-scooter for education purposes	daily	1.1%
	more than 4 times per week	1.1%
	2-4 times per week	3.3%
	1 time per week	2.2%
	1-5 times per month	10.7%
	less than once per month	14%
	never	67.5%
Frequency of using e-scooter for leisure purposes	daily	2.2%
	more than 4 times per week	1.8%
	2-4 times per week	6.6%
	1 time per week	8.9%
	1-5 times per month	21.8%
	less than once per month	36.9%
	never	21.8%
Duration of using e-scooter for commuting within a day	0 minutes	56.1%
	5 minutes	9.2%
	10 minutes	21%
	15 minutes	7%
	20 minutes	4.8%
	more than 20 minutes	1.8%
Duration of using e-scooter for leisure within a day	0 minutes	7.4%
	5 minutes	18.1%
	10 minutes	33.6%
	15 minutes	19.6%
	20 minutes	11.8%
	more than 20 minutes	9.6%

Table 2 presents the responses of the e-scooter users concerning their attitudes about factors that could prevent them from using an e-scooter, while Table 3 includes interventions that could facilitate e-scooter riding and reduce potential negative impacts in the wider society. The average scores in Table 2 are derived based on the respondents' ranking of the factors based on their importance on hindering e-scooter usage (6 corresponds to the most hindering factor and 1 to the least). The data shows that the improper behavior of motorized vehicles drivers is the most important factor preventing them to use e-scooters more frequently. The high score of that factor along with the high score of traffic congestion, highlight some safety issues that users identified. Weather conditions are also an important factor that can prevent e-scooter use. The safety issues are also noted in the responses of needed interventions from improving e-scooter usage and operation, where the implementation of bicycle lanes dominates and the improvement of pavement conditions comes second.

Table 2: E-scooter users' attitudes; factors preventing e-scooter usage

Description	Responses-Options	Scores (Scale 1-6)
Factors preventing the more frequent use of e-scooters	traffic congestion	4.19
	aggressive behavior of motorized vehicles drivers	4.51
	weather conditions	4.37
	air pollution	1.97
	destinations in long distance	3.45
	inadequate connection with other modes	2.46

Table 3: E-scooter users' attitudes; interventions to facilitate riding and reduce negative impacts

Description	Responses-Options	Distribution
Importance of implementing bicycle lanes for improving e-scooter usage and operation	very important	84.5%
	important	14.8%
	not so important	0.7%
	not at all important	0
Importance of implementing scooter parking spots for improving e-scooter usage and operation	very important	20.3%
	important	35.1%
	not so important	38.4%
	not at all important	6.3%
Importance of improving and	very important	59.8%

maintaining pavement condition for improving e-scooter usage and operation	important	34.7%
	not so important	3.3%
	not at all important	2.2%
Importance of implementing traffic signs about scooters for improving e-scooter usage and operation	very important	33.9%
	important	37.3%
	not so important	23.6%
	not at all important	5.2%
Importance of facilitating connection of scooters with other modes for improving e-scooter usage and operation	very important	6.7%
	important	32.2%
	not so important	51.9%
	not at all important	9.3%
Importance of improving and maintaining traffic lighting for improving e-scooter usage and operation	very important	38.9%
	important	40.4%
	not so important	19.6%
	not at all important	1.1%

3.1.2. E-scooter non-users

A similar analysis was conducted for the non-users and presented here. The collected data explores their views regarding issues that emerge from the introduction of e-scooters in the city and means for improving their operation and increasing the likelihood of attracting more users. The sample consists of 45.9% (141) males and 54.1% (166) females. The majority of the respondents (50.8%, 156) belong in the 18-27 age group. Population groups aged over 46 years are underrepresented in the sample. The distribution of the monthly household income for the non-users is somewhat right skewed, since 7,000-12,000 €/year is the most popular answer (24.1%, 74).

Tables 4 – 6 present an evaluation of the perceived issues that emerged from the introduction of e-scooters. The respondents had to rank the different situations by importance; thus, the statistics values in Tables 4 – 6 express average scores. The results show that riding e-scooters on sidewalks is considered an issue of great importance that significantly affects pedestrians' experience. Parking inappropriately on sidewalks is also a pedestrian obstruction. The main issue that vehicle drivers recognize is the fact that riders in many cases do not respect the traffic regulations, despite the fact that they share the same infrastructure with motorized vehicles. The respondents also believe that the movement of e-scooters can be dangerous for vulnerable pedestrians, such as elderly or blind.

Table 4: E-scooter non-users' attitudes; emerging issues for pedestrians' movement

Description	Responses	Scores (Scale 1-4)
Situations hindering pedestrians' movement	riding on sidewalks	3.15
	parking on sidewalks	2.65
	large number of parked e-scooters on sidewalks when demand is low	1.98
	obstructing pedestrian crossing	2.21

Table 5: E-scooter non-users' attitudes; emerging issues for vehicles movement

Description	Responses	Scores (Scale 1-3)
Situations hindering vehicles movement	riding along with vehicles without following traffic regulations	2.64
	illegal parking on roads	1.78
	moving with lower speeds in comparison with other vehicles	1.57

Table 6: E-scooter non-users' attitudes; emerging issues for pedestrians' safety

Description	Responses	Scores (Scale 1-3)
Situations affecting pedestrians' safety	moving with high speeds	2.16
	moving silently	1.64
	dangerous for vulnerable users (e.g. blind)	2.20

The ways for better managing the operation of e-scooters and attracting additional users were also investigated. Table 7 presents non-users' attitudes towards means that could be applied for hindering potential negative effects from the e-scooters usage and for motivating them becoming users. It becomes clear that the respondents consider necessary that every user should have been trained and educated before riding on streets. Regarding the factors that can improve the usage of e-scooters and attract additional riders, it seems that non-users share the same opinion with users and both consider the implementation of bicycle lanes the most crucial.

Based on the average scores that are presented in Table 8, it can be concluded that no significant differences are observed between the means for ensuring that users will comply with traffic regulations. However, the highest importance is assigned to the imposition of fines.

Table 7: E-scooter non-users' attitudes; potential improvements

Description	Values	Distribution
Users training and education is needed	yes	71.7%
	no	28.3%
Importance of implementing bicycle lanes for becoming a user	very important	75.8%
	important	14.7%
	not so important	4.9%
	not at all important	4.6%
Importance of implementing scooter parking spots for becoming a user	very important	24.8%
	important	33.2%
	not so important	25.1%
	not at all important	16.9%
Importance of implementing traffic signs about scooters for becoming a user	very important	36.8%
	important	30%
	not so important	23.4%
	not at all important	9.8%
Importance of improving and maintaining traffic lighting for becoming a user	very important	35.3%
	important	27.5%
	not so important	19.6%
	not at all important	7.6%

Table 8: E-scooter non-users' attitudes; means to ensure traffic regulation compliance

Description	Values	Scores (Scale 1-4)
Means for ensuring compliance with traffic regulations	suspension of account for incidents	2.55
	imposing fines	2.79
	notification for inappropriate parking	2.50
	speed reduction	2.17

Table 9 presents the factors that prevent respondents from becoming e-scooter users. Respondents had to rank the factors by their importance, with 1 corresponding to the least important and 5 to the most important factor. The responses underscore the lack of adequate infrastructure in the city, which is necessary for enhancing e-scooter usage and micromobility, in general. It seems that the rental cost is also an important barrier, since in comparison with Thessaloniki's public transport, e-scooters are a more expensive option. On the other hand, the existence of different companies with relatively large fleets results in a high number of e-scooters distributed throughout the city, that can be easily accessed and therefore the availability of e-scooters is not an important reason for not becoming a user. It should be also noted that many respondents (35.5%) consider the protection of personal data as a barrier for using an e-scooter.

Table 9: Reasons for not using e-scooters

Description	Responses	Scores (Scale 1-5)
Factors preventing the use of e-scooters	lack of infrastructure	4.15
	limited number/availability of e-scooters	2.12
	cost	3.49
	need for a credit card	3.00
	need for a smartphone	2.23

3.1.3. Comparison of users and non-users' attitudes

The descriptive analysis presented in Sections 3.1.1 and 3.1.2 shows that the attitudes of users and non-users are very similar. Their responses indicate that factors associated with safety and comfort are of the greatest importance in deciding to ride an e-scooter. For users, the issue of safety and comfort is highlighted by the very high score (4.51 of 6) indicating that aggressive behavior of motorized vehicles drivers is the most critical factor preventing them to use an e-scooter, as well as by the very high percentages expressing the need for implementing adequate facilities (i.e., bicycle lanes). For non-users, the essential role of safety and comfort is revealed by identifying the lack of infrastructure as the main reason for not using e-scooters, but also by pointing that the implementation of bicycle lanes and the realization of training and education activities as the two most important actions for improving the use of e-scooters within cities. Especially, the implementation of bicycle lanes suitable for hosting also micromobility vehicles seems to be the first priority for both users and non-users.

The way users and non-users evaluate the importance of implementing traffic signs for e-scooters, traffic lighting and parking spots for e-scooters is similar. More specifically, both users and non-users recognize traffic signs for e-scooters and lighting as important interventions that could facilitate the usage of e-scooters and mitigate potential negative impacts. However, the importance they assign to them is much lower compared to the implementation of bicycle lanes. On the other hand, the implementation of parking spots for e-scooters does not seem to assist the shift of travelers to e-scooters, probably indicating that the dockless nature of these systems meets sufficiently their needs.

3.2. Identification of the attracted users' profile

The classification tree analysis was carried out using the R programming language for statistical computing (R Core Team, 2017). More specifically, the tree package (Ripley, 2019) was used for the development, the evaluation and the optimization of the classification tree. The first step in the model development was to separate the data in a training and a test set. A separation of 70% (195 observations) training set and 30% (83 observations) was considered appropriate for having a reasonable number of observations in each set and therefore to avoid failures in the variable selection or high variance in the performance statistics. In order to avoid overfitting, which is a potential disadvantage of the decision tree models, tree pruning was applied. The post-pruning approach was selected, meaning that a full tree was first developed and then some of its lower parts were removed (Bramer, 2013). For the removal of the tree lower parts, the 10-fold cross-validation method was applied and it was sought to identify the optimal number of terminal nodes by minimizing the classification error. Through this process, the optimal size of the tree derived and the classification tree presented in Figure 3 was developed. The performance of the model was assessed by comparing its predictions with the test set values resulting in a prediction accuracy equal to 65.1%.

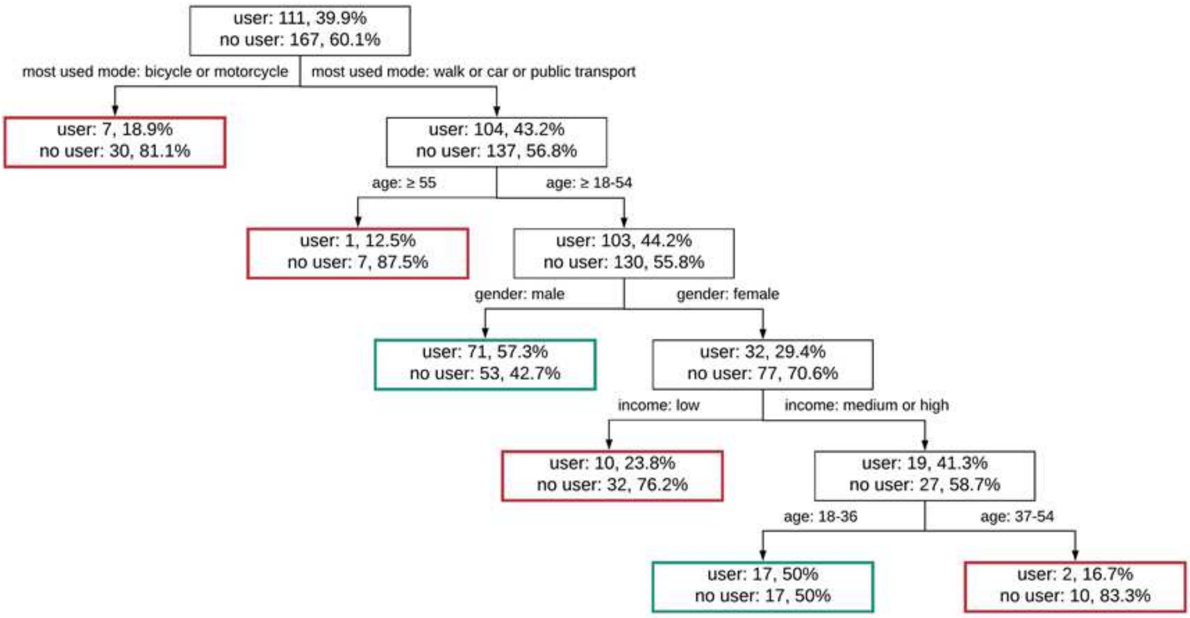

Figure 3: Classification tree for distinguishing e-scooter users by non-users

The frequencies and the percentages of the two categories in each node of the tree were derived from the total sample and by following the conditions that are indicated by the developed model (terminal nodes with red outline show segments of the population with low likelihood of being attracted; terminal nodes with green outline show segments of the population with relatively high likelihood of being attracted). The results of the classification tree indicate that the respondents' most commonly used transport mode, age, gender and income can be used to differentiate between attracted e-scooter users and non-users. It should be noted that the nodes located at the top of the tree indicate the most important variables of the model. Therefore, based on Figure 3 the results of the classification tree can be interpreted and summarized as following:

- The respondents' most frequently transport mode they use for their trips is the most significant predictor. People using bicycle or motorcycle are not as much attracted by the shared e-scooters novelty, while people traveling on foot, private car or public transport are more likely to use e-scooters more than once.

- Older persons (i.e., age over 55) are not attracted by e-scooters. The likelihood of being attracted by e-scooters is higher for people between 18 and 36 years. It is noted that the age classes used for the analysis are identical with those provided in the questionnaire (i.e., 18-27, 28-36, 37-45, 46-54, and ≥55) and the grouping of some of the classes as noted in Figure 2 is an outcome of the classification tree analysis.
- Males with ages aged between 18 and 54 and who are not bicycle or motorcycle frequent users, are likely to be attracted by e-scooters.
- Income also has some impact, but not very strong. People of lower income have a lower likelihood to be attracted by e-scooters. In this study, low income corresponds to values lower than 12,000€/year, medium income is between 12,000 and 24,000€/year, and high income reflects values greater than 24,000€/year. It is also noted that the interpretation of the income variable should be treated cautiously, since it was entered in the late stages (nodes) of the classification tree and this reflects a limited sample.

3.3. Identification of the engaged users' profile

The identification of the engaged users' profile was approximated via a latent variable model where the questionnaire responses related to the frequency of use, with respect to the various trip purposes, were considered as underlying indicators of engagement; higher engagement of an individual is reflected in higher frequency of use. This approach was decided considering the questionnaire design in an effort to conduct a deeper investigation of engagement by examining frequency of use per trip purpose rather than using a single generic question (i.e., overall trip frequency) for the same purpose. Following this framework, a latent variable that represents engagement was defined as (Equation 1)

$$LV_n=h(Z_n,\delta)+\omega_n \tag{1}$$

where $h(Z_n,\delta)$ is a linear function of explanatory variables Z_n and δ their parameters to be estimated, while ω_n is a normally distributed disturbance. It should be mentioned that for model identification purposes (Vij and Walker, 2014), the variance of the disturbance term was fixed equal to unity.

The variables used as indicators and presented in Table 1, all had an ordered form. The ordinal nature of the indicators allows for representing the probability of a specific response following the specification presented in Daly et al. (2012). The measurement equations of a K-level indicator I_{mn} for respondent n (of total M indicators), with levels i_1, i_2, …, i_K are specified as a function of τ_{m1}, $\tau_{m,2}$, …, $\tau_{m,K}$ thresholds that need to be estimated.

$$I_{ln}=\begin{cases} i_1 & \text{if} \quad -\infty<LV_n\leq\tau_{m,1} \\ i_2 & \text{if} \quad \tau_{m,1}<LV_n\leq\tau_{m,2} \\ & \quad \vdots \\ i_k & \text{if} \quad \tau_{m,(K-1)}<LV_n<\infty \end{cases}$$

The likelihood of an observed indicator value is given as (Equation 2):

$$L_{I_{mn}}=I_{(I_{mn}=i_1)}\left[\frac{\exp\left(\tau_{m,i_1}-\zeta_m LV_n\right)}{1+\exp\left(\tau_{m,i_1}-\zeta_m LV_n\right)}\right]+\sum_{k=2}^{K-1} I_{(I_{mn}=i_k)}\left[\frac{\exp\left(\tau_{m,k}-\zeta_m LV_n\right)}{1+\exp\left(\tau_{m,k}-\zeta_m LV_n\right)}-\frac{\exp\left(\tau_{m,(k-1)}-\zeta_m LV_n\right)}{1+\exp\left(\tau_{m,(k-1)}-\zeta_m LV_n\right)}\right]+I_{(I_{mn}=i_K)}\left[1-\frac{\exp\left(\tau_{m,(K-1)}-\zeta_m LV_n\right)}{1+\exp\left(\tau_{m,(K-1)}-\zeta_m LV_n\right)}\right] \quad (2)$$

where ζ_m measures the effect of the latent variable on indicator I_{mn}. Model estimation involved the joint likelihood maximization of all indicators conditional on the latent variable. The unconditional log-likelihood function included integration over ω as shown in Equation 3

$$LL=\sum_{n=1}^{N}\ln\int_{\omega}\left(\prod_{m=1}^{M}L_{I_{mn}}\right)f(\omega_n)d\omega \quad (3)$$

The model was estimated using an adapted version of the Apollo R package (Hess and Palma, 2019). The integral was approximated with simulation using 1000 Halton draws (Halton, 1960).

The descriptive statistics analysis presented in Table 1, showed that for all types of trip purpose, with the exception of entertainment/leisure, the most frequent answer was ‘never’. Moreover, the responses related to higher frequency use had significantly fewer responses. These trends could lead to potential estimation issues and reduction of the explanatory power of the model as a result of lower frequencies for specific indicator values. Hence, the values of the original questionnaire were recoded in fewer categories. The new categories and their interpretation are presented in Table 10.

Table 10: Original and revised categories of the latent variable indicators

Original categories	Revised categories
Every day More than 4 times per week 2-4 times per week	2 or more times per week
1 time per week 1-5 times per month	1-5 times per month
Less that once per month	Less that once per month
Never	Never

The revision process resulted in four categories, related to frequency of e-scooter use, instead of six, which was the initial number. As shown in Table 10, the categories “Less than once per month” and “Never” remained the same as the original. The “1-5 times per month” and “1 time per week” categories were merged into a single group as they both represent similar frequency of use. Finally, the remaining categories related to higher frequencies of use were combined in a single group to ensure adequate sample size for those respondents. In addition to the indicators, some further recoding was necessary for some of the explanatory variables of the model. In particular, only one respondent was in the over 55 age category. This person was included in the 46-55 age group, as estimation of a parameter for the original category was infeasible with a single observation. Moreover, the residency area was grouped in five categories, with respect to proximity to city center. This was achieved using the municipality of Thessaloniki boundaries to define the "city center"; the municipalities that share a boundary with the municipality of Thessaloniki formed the "close to center" category and those not bordering with the municipality of Thessaloniki formed the "far from city center" category. It is worth mentioning that the question regarding residency area was included only in the electronic version of the questionnaire. However, residency area is likely to have an effect on e-scooter use and engagement, as most of the facilities are located in the city center. Hence, the missing values were treated as a different category and included in the model. This category does not have any particular interpretation; however, it allowed the inclusion of this variable in the model specification without reducing the sample size. Table 11 presents the explanatory variables that were finally included in the model, along with their reference category. These refer to the Z_n variables reported in Equation 1.

Table 11: Explanatory variables of the engagement model

Variable	Categories	Reference
Gender	Female, Male	Male
Age	18-27, 28-36, 37-45, 46+	18-27
Area of living	City center, Close to city center, Far from city center, Other, Missing	City center
Traffic congestion	Not at all important, Not so important, Somewhat important, Important, Very important, Extremely important	Extremely important

The parameter estimates related to the impact of the individual characteristics on the engagement latent variable are presented in Table 12. These refer to the vector δ defined in Equation 1. With respect to gender, female respondents were less likely to be frequent e-scooter users compared to males (significant at the 0.1 level). Regarding age, a significant difference occurred between users of 28-36 and 18-27 age categories, as the former were less likely to be engaged in the use of e-scooters. No other significant differences were noted concerning age. This could be attributed to the low sample size of the remaining age groups, as noted above.

Despite the inconsistencies in the parameter signs related to the age groups, the results related to the older groups are not significant and thus not reliable for further interpretation. In regard to the residency area, all areas had a negative impact compared to city center. Although the only significant difference was observed between city center and areas close to the city center, the overall negative trend of all parameters might indicate that city residents outside the city center area are less frequent users of e-scooter. Finally, respondents that considered traffic congestion as an extremely important issue of less frequent use of e-scooter, were also less likely to be engaged. Although this might seem counter-intuitive, since the use of e-scooters allows for additional flexibility and the possibility to weave through traffic avoiding congestion and thus saving time, safety concerns may be the main reason for lack of engagement. E-scooter riders are vulnerable road users and may not feel comfortable sharing the road with motorized vehicles because of drivers' behavior. This was also reflected in the descriptive statistics analysis (Table 2) where the behavior of motorized vehicles drivers and traffic congestion were two of the most important reason that discourage respondents from using e-scooter.

Table 12: Parameter estimates of the Engagement latent variable

Variable	Estimate	Rob.t-ratio (0)
Female dummy	-0.3213	-1.77
Age: 28-36	-0.5445	-2.11
Age: 37-45	0.2101	0.56
Age: 46+	0.0670	0.08
Area: Close to city centre	-0.8433	-2.82
Area: Far from city centre	-0.6684	-1.49
Area: Other	-0.6965	-1.10
Area: Missing	-0.3314	-1.28
Traffic congestion: Not at all important	1.0061	3.35
Traffic congestion: Not so important	1.3039	3.56
Traffic congestion: Somewhat important	0.5874	2.27
Traffic congestion: Important	0.5580	2.35
Traffic congestion: Very important	0.3299	1.46

The parameter estimates related to the impact of the latent variable on the indicators (ζ_m) and the threshold parameters of the indicators ($\tau_{m,k}$) are presented in Table 13. All ζ_m parameters were significant and had a negative sign. This finding is consistent with expectations as an increase in the value of the latent variable was related to lower categories of the indicators which, based on the data structure, represented higher frequencies of e-scooter use. The significant ζ_m parameters also indicated that all trip purposes could be used as indicators of e-scooter engagement.

Table 13: Parameter estimates of the measurement equations

Variable	Estimate	Rob.t-ratio (0)
$\zeta_{education}$	-1.2019	-3.22
ζ_{work}	-1.1815	-3.90
ζ_{home}	-1.7904	-3.24
$\zeta_{entertainment}$	-0.5959	-3.61
$\tau_{education,1}$	-3.5480	-5.96
$\tau_{education,2}$	-1.8675	-4.02
$\tau_{education,3}$	-0.8997	-2.26
$\tau_{work,1}$	-3.2189	-5.64
$\tau_{work,2}$	-1.5603	-3.70
$\tau_{work,3}$	-0.8381	-2.21
$\tau_{home,1}$	-2.8876	-5.27
$\tau_{home,2}$	-0.3613	-0.77
$\tau_{home,3}$	1.3934	2.15
$\tau_{entertainment,1}$	-2.2684	-8.86
$\tau_{entertainment,2}$	-0.2838	-1.34
$\tau_{entertainment,3}$	1.4636	5.99

4. Conclusions

The analysis conducted here allowed for the determination of the user profiles and attitudes towards e-scooter use and provide a peek into the reasons for been engaged in e-scooter use. The analysis concludes that:

- The vast majority of trips that are now being conducted with a shared e-scooter would have been conducted on foot or with public transport if the e-scooters were not available. This result is in full agreement with previous research in the other European cities such as Vienna, Austria (Laa and Leth, 2020) and Munich, Germany (Sellaouti, Arslan and

Hoffmann, 2020), as well as with the results of a study in Calgary, Canada which identifies that almost half trips would have been completed on foot (City of Calgary, 2020). However, this finding is interestingly in contrast with what studies from U.S. cities point out (San Francisco Municipal Transportation Agency, 2019; Portland Bureau of Transportation, 2018). The concordance of the results from the European cases questions the positive impact of e-scooters on the environment, since Hollingsworth, Copeland and Johnson (2019), as well as Kazmaier, Taefi and Hettesheimer (2020) state that the reduction of the negative environmental impacts is closely linked to the transport modes that they replace. In this case, they tend to replace environmentally friendly modes (walking and public transport) and thus their environmental impact may not be as great as it was initially envisioned.

- People traveling with bicycle or motorcycle are less likely to be attracted as a novelty by shared e-scooters and to attempt their use. The new transport mode seems to provoke fascination to those moving on foot, with private car and public transport, but not to those already moving with traditional light vehicles such as bicycle and motorcycle.
- Males are more likely both to be attracted and to be engaged with the new mobility option than females. This is in agreement with almost all prior studies (Denver Public Works, 2019; San Francisco Municipal Transportation Agency, 2019; Laa and Leth, 2020) showing that e-scooters increase the gender mobility gap instead of bridging it. This may be indicative of the potential risk related to driving an e-scooter and the greater risk-taking behavior of males as it has been demonstrated in other research. The combination of these two facts could explain the higher likelihood of males to use an e-scooter.
- Older persons found to be unwilling to attempt to use this new transport mode, but this finding should be treated cautiously due to the limited responses obtained from this age group. However, the results from the latent variable logit model showed that older persons that attempted to ride an e-scooter in many cases became frequent users. The greater

tendency of younger persons to use e-scooters is commonly accepted in the literature coming from both continents (San Francisco Municipal Transportation Agency, 2019; Baltimore City Department of Transportation, 2019; City of Santa Monica, 2019; Caspi, Smart and Noland, 2020; Laa and Leth, 2020).

- People living in long distance from the city center rarely engage in using e-scooters. This conclusion can be attributed to two different reasons. First, there is an easier access to e-scooters in the city center, since micromobility operators tend to allocate the majority of e-scooters in city center and in locations close by. This is mainly done due to the presence of land uses that concentrate high demand and these areas are in many cases in the downtown. Second, the mix of land uses is more intense in the inner city compared to areas that located further away that are mainly characterized as residential land use. This mix of land uses gives residents of the inner city the possibility to perform many of their activities in a short distance and consequently reach them through e-scooters. Higher e-scooter usage in downtown was also identified by a study that analyzed e-scooter trips in Austin, Texas and Minneapolis, Minnesota (Bai and Jiao, 2020).
- Both users and non-users identified the lack of infrastructure as a critical aspect of not utilizing e-scooters more frequently or been attracted to use them. This is a critical component in the successful implementation and wider use of this micromobilty service, if cities are interested in utilizing it as part of their mobility solutions arsenal. Infrastructure improvements could include developing more facilities for micromobility vehicles, providing more organized parking areas, and improving pavement surfaces. Some of these elements will also alleviate the possible conflicts between e-scooters and pedestrians. This conclusion in addition to the consideration of the regulatory framework that was developed in Greece (which equates e-scooters with bicycles) and users' preferences for riding on bike paths and lanes (as it is identified in the literature (City of Calgary, 2020)), it becomes

evident that bicycle lanes are a necessity, since they have now to “host” additional and divergent users.

Transportation city agencies could use the findings presented here and start considering policies that could influence e-scooter users. For example, the fact that older individuals could become frequent users once they use e-scooters even though they are less likely to be attracted to them, is a critical information for establishing demonstration trips or activities targeting non-traditional users and thus providing them with an alternative transport mode to complete their mobility needs. Educational activities and campaigns could be also developed based on the findings of the study and targeted to specific population segments and present proper use etiquette and rules of the road. This may be more critical for the younger users, since they may lack the knowledge of the traffic code and thus ignore several of the dangers of the e-scooter use and the problems that could result from improper use.

Another important outcome of the analyses is that e-scooters can trigger some urban mobility inequalities. These inequalities can be based on the gender or the place of residence. Agencies and local authorities have to bridge the inequalities by forming safer places for e-scooters in order to make them an attractive mobility option for females, which in most cases have a more cautious behavior, but also to establish appropriate regulations for the e-scooter sharing companies to provide sufficient access to the residents of the whole city.

These findings point out the need to expand the sample size and collect additional data that could shed further light in identifying the user profiles and engagement reasons. The study conducted here demonstrated an approach for completing similar efforts. However, having a larger sample would allow for a more robust evaluation of similar issues and provide a sturdier foundation to guide agencies in developing their policies. Moreover, a larger sample would allow the development of a more accurate decision tree for classifying users and non-users. The prediction accuracy of the classification tree used here also shows that there may be some additional variables that affect travelers' decision to use an e-scooter and that could be an area for further investigation. In addition, for the examination of users' engagement, the research accomplished here opted to mainly focus on demographic and socioeconomic characteristics of the respondents. It is anticipated that variables concerning the perceptions of users when riding can also explain their willingness to become frequent e-scooter riders. These perceptions could be closely related to safety and comfort, but they can also concern well-being aspects. Educational and training programs aiming to promote the proper use of micromobility vehicles could also have an impact on e-scooter engagement. The potential positive impact of education and training was already indicated in the descriptive statistics presented in Table 7. Future research could also use rental data and apply spatial modelling techniques for revealing the relationship between shared e-scooters usage and characteristics of the built environment. Even with these limitations, the current study contributes to the body of literature by defining a robust statistical approach to evaluate and define shared e-scooter profiles and underscores the need for a framework of their operation as well as the necessity to expand bicycle facilities to accommodate their future expansion.

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