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Examination of the Effects of the Pandemic Process on the E-scooter Usage Behaviours of Individuals with Machine Learning

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ABSTRACT: Analysing user behaviour and thus travel mode choice is an important task in transport planning and policy-making in order to understand and predict travel demand. Recent pandemic events have challenged the modal choices of European users by reducing the use of public transport at various times and favouring walking and/or the use of electric bikes and scooters for last-mile travel. A number of studies have focused on analysing how the pandemic affected workers' choice of transport mode, with particular reference to local public transport, by developing multinomial logistic regression and artificial neural network models to analyse travellers' choice of transport mode before and after COVID-19. Particularly in non-European contexts, studies have been conducted on the relationship between socio-economic factors and the duration of e-scooter trips before and during the health crisis caused by the pandemic. in these contexts, a general increase in the duration of e-scooter trips after the pandemic was shown. Few studies, however, have analysed the European context.

Several factors relating to services and infrastructure as well as socio-demographic components contributed to the propensity to use e-scooters as evidenced by a number of literature works in the European context. However, little research has been conducted using the machine learning approach to understand which factors and how they may influence modal choices. The present research work focused on the analysis of last-mile transport choices by investigating the propensity of a sample of users residing in Sicily during different time phases before and after the COVID-19 pandemic. In this study, 35 different classes were determined for a total of 545 data. The classification process was carried out using SMO, KNN and RF machine learning algorithms.

The results showed a reduction in the frequency of e-scooter use during the health crisis caused by the pandemic. The results showed that this was a temporary behaviour, even though the purpose of e-scooter use by most individuals changed during the health crisis caused by the pandemic. However, it was observed that the frequency of e-scooter use decreased in most individuals during the health crisis caused by the pandemic and this became a permanent behaviour.

The results suggest that the analysis of the importance of variables in relation to different periods and is essential for a better understanding and effective modelling of people's travel behaviour and for improving the attractiveness of these means of transport for companies operating services in the areas examined.

KEYWORDS: E-scooter; Machine learning; Pre-post COVID-19 travel behaviour; Mobility choices; Sicily

1. INTRODUCTION

Since the beginning of the pandemic, the number of trips by electric scooter has increased by about 70 % as confirmed by a number of shared scooter service companies in Italy. Indeed, several works in the literature have pointed out that mobility needs have changed drastically due to the coronavirus, including alternative mobility. This has highlighted the continuous decline in the number of passengers on public transport (Caballini, Agostino, Dalla & Chiara, 2021; Moslem et al., 2020).

The pandemic has reduced large trips, but within the shared mobility sector, smaller and heavier vehicles have grown, especially electric scooters. However, these services are still unevenly distributed across the Italian peninsula.

Some studies argue that shared mobility has significant potential to reduce CO2 emissions from transport and thus the negative impact of human presence on the environment (Tikoudis et al., 2021; Kubik, 2022). Moreover, it is a fully digitised sector.

The crisis caused by COVID-19 has led millions of people to look for new alternatives to make their daily journeys such as those to university or their workplace, while respecting the rules regarding distancing. Modal choices have changed not only because of restrictions imposed by different governments (e.g. onboard contiguity and respect for social distancing) but also because of increasing work from home and online education (Campisi, et al., 2022a; Faıyetole, 2022; Ravalet & Rérat, 2019).

To cope with the increased demand, several companies operating shared electric scooter services have also thought of new forms of subscription and made the service free of charge in some months to certain users such as health workers. Since 2022, there has been a resurgence and revival in the use of urban and non-urban public transport such as buses and trains (Caselli, Fracasso & Scicchitano, 2022).

While micro-mobility has been a major player in post-pandemic transport, national strategies to revitalise the economy after the COVID-19 pandemic, in order to enable the country's green and digital development, such as the National Recovery and Resilience Plan (PNRR) has paid special attention to last-mile mobility and allocated several funds to incentivise the use of scooters and alternative battery-powered vehicles (Ingoglia, 2022; Vitetta, 2022).In order to be able to promote the national implementation of better and more widespread intermodality, it is necessary to better analyse the factors that change user behaviour for the various modes of transport, starting with those used for the last mile. This can enable users to move around the city using more sustainable means of transport, perhaps with the help of a digital system.

This research work focuses on evaluating the factors affecting the use of e-scooters in Sicily in the post-pandemic phase through the realisation and administration of a questionnaire and through a machine learning approach as better described in the following paragraphs. This study is organised as follows. Section 1 reviews an introduction on the demand for the use of e-scooters. Section 2 reviews the literature in the European context regarding e-scooters as a modal choice during different pandemic phases. Section 3 explains how the data were collected and processed, how the demand analysis unit was set up, and which methodologies were used to predict demand. In Section 4, we present the results of demand forecasting based on the unit of analysis defined in Section 3. Finally, in Section 5, we briefly summarise the results of this study, cite its implications and limitations, and suggest future research directions.

2. BACKGROUND

Since 2020, the popularity of shared e-scooters has grown rapidly throughout Europe, with various environmental and socioeconomic benefits. In general, there is a need for more research on the demand and supply of electric shared scooter services to further optimise e-scooter mobility services for transport planners and micro-mobility operators. At the moment, little attention has been paid to a comprehensive comparison of e-scooter sharing mobility in different cities. As confirmed by a study conducted by Li et al. (2022), similarities and differences in e-scooter sharing mobility were highlighted by collecting and analysing vehicle availability data from 30 European cities during the post-COVID-19 pandemic. Comparisons were made considering temporal travel patterns, statistical characteristics (distance and travel time), utilisation efficiency and electricity wastage during the idle period. The results suggest that similarities and differences coexist between e-scooter sharing services in cities, and utilisation efficiency is significantly correlated with the number of e-scooters per person and per unit area. In particular, a study conducted in Stockholm, Ali (2021) analysed the behaviour of E-scooter users on the basis of a survey investigating user characteristics in terms of preferences and analysis of key travel parameters. The survey was designed to cover most behavioural influencing factors. Time and cost of travel were highly valued by the users and were considered as decision criteria before making a trip; with regard to normal travel, it was found that walking most often replaces the use of e-scooters. Historical data were used to validate and support the survey results. The survey questions did not consider the impacts of COVID-19 on travel behaviour and changes in travel patterns. In addition, research areas such as safety, including the adoption of risky behaviour and helmet use, were not highlighted. Also in Northern Europe, the study conducted by Pazzini et al. (2022) examined the speed and behaviour of e-scooter drivers in the city of Trondheim (Norway) to understand how to manage this mode of transport. Through a series of sensors, these data were acquired considering socio-demographic data such as gender, age and data relating to the use of scooters such as distance to pedestrians and speed and its adaptation to the environment and type of vehicle used. Through an analysis with a logit, binomial model, the data obtained were used to analyse the type of road infrastructure preferred by e-scooter drivers. The results showed that the cycle track is most used and the modal choice was mainly dependent on the road environment.

A literature review was conducted by Dias, Arsenio & Ribeiro (2021) focusing on the working principle of the e-scooter system in the city of Braga, Portugal. It has been determined that this e-scooter system has objectives such as reducing air pollution in cities, reducing inequalities in access to transportation, encouraging economic savings and increasing mobility. It has also been revealed to allow for shared e-scooter modes as a post-pandemic mobility option, even incentivizing special fees for people to start using the service.

A study of strategies implemented for the introduction of e-scooter sharing systems in different operational areas in Germany was conducted by König, Gebhardt, Stark & Schuppan (2022). An interview study with 21 stakeholders with different backgrounds (local transport authorities, public transport providers, e-scooter sharing operators, municipalities, associations, planning offices and consulting companies, and other mobility providers) was conducted to reflect upon the introduction of e-scooter sharing systems in Germany and stakeholders' involvement in planning.

In another study on this subject, besides the travel patterns of e-scooter users, the willingness of standard scooter users to switch to e-scooter for different hypothetical scenarios was analyzed and the factors affecting the users' desire to switch were made. Standard descriptive statistical methods, McNemar-Bowker test on paired samples, and multinomial logistic regression were used in the analysis of the study (Glavić, Trpković, Milenković, & Jevremović, 2021). This study identified certain factors that have a positive (environmental benefits, avoidance of congestion) and negative (safety problems, lack of infrastructure, etc.) impact on users' willingness to switch to e-scooters.

With regard to Southern Europe, a study showed the trend of owning, renting or sharing e-scooters in Palermo by Campisi, Akgün-Tanbay, Md Nahiduzzaman, & Dissanayake, (2021) and, again for the same city, a study conducted by Akgün-Tanbay, Campisi, Tanbay, Tesoriere, & Dissanayake (2022) analysed the perception of safety, comfort and chaos perceived by users who used shared spaces (pedestrians, cyclists and scooter users). Both studies analysed socio-demographic variables relating to potential users of the service and confirmed that the majority of users are male and emphasised that the use of shared spaces is perceived by females as less safe and therefore less likely to use scooters.

In Italy, the use of e-scooter is recent, and its regulation is not yet complete. As far as the Italian context is concerned, some studies have focused on evaluating the strengths and weaknesses relating to the use of scooter services according to different points of view: the operator's point of view, the policy-maker's point of view and the user's point of view, and investigating both the Rome (Carrese, Giacchetti, Nigro, Algeri, & Ceccarelli, 2021) and Palermo (Campisi, Tesoriere, Trouva, Papas & Basbas, 2022b) areas.

The results of both researches point to a precompetitive phase of the e-scooter sharing market in Italy compared to the United States and Europe, with different differences between cities and the need to pay attention to acts of vandalism that can jeopardise the use of these means of transport. In recent years, a number of researches have investigated how artificial intelligence can be used to improve the provision of transport services (Kuşkapan Çodur, & Atalay, 2021). In particular, through the use of machine learning, it is possible to make predictions based on available data such as that of shared scooters.

For example, the variables influencing the accidents suffered by e-scooter users and the estimation of the probability of an accident while travelling with an e-scooter were analysed in different cities in Turkey by testing the effects of input parameters with statistical data analysis and estimating the probability of an accident with an e-scooter with machine learning and finally calculating the optimal values of input parameters to minimise accidents with e-scooters (İnaç, 2023).

A study conducted by Zhao, Li, Pilesjö, & Mansourian (2022) applied methods such as logistic regression, artificial neural network and random forest to predict the usage efficiency by inputting a set of service features. It proposed a machine learning approach to predict the usage efficiency of shared e-scooters using GPS-based vehicle availability data while applying three typical machine learning methods, including logistic regression, artificial neural network, and random forest, to predict usage efficiency by inputting features. This study showed that the results obtained can be useful for micro-mobility operators and planners to design policies and strategies to further improve the usage efficiency of e-scooter sharing services. Strategies to improve e-scooter sharing services are still a major concern for micro-mobility operators and urban planners. Several studies have used the selection of specific variables characterising transport demand or the variability trend in different periods using machine learning methods to investigate correlations between variables and their prediction The present work starts from the conception of wanting to investigate the post-pandemic behaviour of users of e-scooters in Sicily using machine learning techniques. A small number of studies currently present in the Italian literature analyse this topic.

3. METHODOLOGY

3.1 Machine Learning

Machine learning is a sub-branch of artificial intelligence in computer science. Machine learning is frequently used in numerical learning and recognition studies. It allows making various predictions on the data based on known features in the data set. While performing this process, it takes human behaviour as an example (Carbonell, Michalski, & Mitchell, 1983). In this way, the perception process can be carried out successfully through experience. Today, machine learning has started to be used in almost every field (Bell, 2022). However, thanks to its frequent use in the field of engineering, its use is becoming more and more widespread thanks to the fact that desired results can be obtained quickly and practically without the need for a lot of labour (Kuşkapan, Sahraei, Çodur, & Çodur, 2022).

Machine learning contains many algorithms. Each of these algorithms examines the existing dataset from different aspects. There are various criteria to determine the performance of an algorithm in machine learning. The concepts of mean absolute error (MAE), root mean squared error (RMSE) and kappa statistic are expressed as error criteria. The fact that the MAE and RMSE values are low and the kappa statistic value is high in an algorithm reveals that the error of that algorithm is low.

The formulas used in calculating the error criteria are given in equations 1-2-3 below. In kappa statistics, p_o and p_e are expectation and observation, respectively. In MAE and RMSE, $x_{f,i}$ and $x_{o,i}$ are the i_{th} expectation and observation, respectively.

$$(1)\quad MAE = \frac{1}{N}\sum_{i=1}^{N}\left(x_{f,i} - x_{o,i}\right)$$

$$(2)\quad RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\left(x_{f,i} - x_{o,i}\right)^2}$$

$$(3)\quad K = \frac{p_o - p_e}{1 - p_e}$$

In machine learning, the concepts of precision, recall, f-measure, and receiver operating characteristic (ROC) area are expressed as performance criteria. Confusion matrix is used to calculate the precision, recall and f-measure criteria. The confusion matrix is given in Figure 1 below.

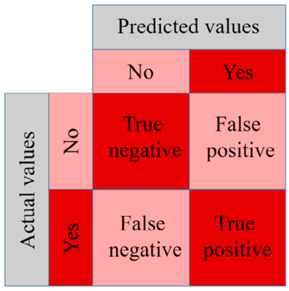

Figure 1. Confusion matrix

Precision, recall and f-measure criteria can be calculated by using the actual and predicted values given in the confusion matrix. The ROC area is obtained with the curve created to interpret the model performance in general. All of these performance values take values between 0 and 1.

The high precision, recall, f-measure, and ROC area values in an algorithm reveal that the algorithm has a successful performance (Bradley, 1997). Precision, recall and f-measure concepts can be calculated by using the equation 4-5-6 below.

$$(4)\quad Precision = \frac{True\ Positive}{True\ Positive + False\ Positive}$$

$$(5)\quad Recall = \frac{True\ Positive}{True\ Positive + False\ Negative}$$

$$(6)\quad F - measure = \frac{2 \times Recall \times Precision}{Recall + Precision}$$

In this study, to examine the results of the survey presented for a total of 545 individuals, more than one machine learning algorithm has been used. In the study, the current data set has been analysed by Sequential Minimal Optimization, Random Forest, and K-Nearest Neighbors algorithms respectively and these algorithms have been compared in terms of both error criteria and performance values.

3.2 Sequential Minimal Optimization

Sequential Minimal Optimization (SMO), a subhead of support vector machines, is a method that can quickly solve the optimization problem without the need for any extra matrix system. This algorithm selects two Lagrange multipliers at each step and updates the most suitable values for these multipliers. Since this method does not use any matrix algorithm, it is less precision for studies that require numerical sensitivity. In addition, the algorithm changes all loss values with a new one, as well as normalizing attributes with predefined values (Platt, 1998).

3.3 Random Forest

Random forest algorithm is a supervised classification algorithm and can also be used in regression problems. This algorithm aims to successfully classify by generating more than one decision tree in the analysis process. It is possible to obtain more successful results as the number of trees increases (Biau & Scornet, 2016). Various models are produced by training each decision tree on a different observation sample. Voting is performed for each value as a result of the estimation in the models created. Finally, the result is obtained by choosing the most voted value for the prediction (Rigatti, 2017).

3.4 K- Nearest Neighbors

The k-nearest neighbour algorithm is used to reveal the class of an observation that will be added to the data set by making use of the observation values in a cluster with certain classes. In this algorithm, the k nearest neighbours of an unknown taken for classification are determined (Laaksonen & Oja, 1996). By looking at the classes in which these neighbours are located, the class to which the unknown to be classified is closest is determined. Euclidean distance or cosine similarity is used when determining the nearest neighbour value (Kramer, 2013). The most used k values are 3, 5 and 7, depending on the size of the dataset

3.5 Data Processing

The authors implemented in March 2023 a questionnaire taking into account the variability of displacements that have occurred and have been described in the literature during the period 2020-2023, taking into account the recent pandemic from COVID-19. In order to compare the motivation for displacement with the frequency during 3 different periods, i.e. pre-pandemic, during and post-pandemic periods, i.e. from before March 8, 2020, from March 8, 2020 until December 2022 and since January 2023. The questionnaire was constructed by requesting frequencies of use on a Likert scale and taking into account the main motivation for travel and frequency as they varied over the three periods listed above.

In particular, frequency was estimated using the following scale:

- rarely (once or twice a month)
- once a week
- twice a week
- once a day
- two or more times a day

The entire sample is connected to the Sicilian regional context. It is related to users with experience in the use of e-scooters and subscribers to Sicilian social channels (Facebook) on the use of electric scooters.

About 35% of the members of the social page answered the questionnaire. The questionnaire was constructed following a series of questionnaires implemented for other research by the authors, emphasising the importance of associating travel motivation with frequency for the mode of transport analysed. In addition, this questionnaire is based on the concept of a low percentage of questionnaires in the local area that associate the study of these variables especially in the pre- and post-pandemic phase.

Approximately 2’101 road accidents including injuries to people including at least one electric scooter were recorded in Italy. Approximately 564 incidents were recorded as of May 2020. There was a total of 9 fatalities, plus a pedestrian who was run over and died, and approximately 1’980 injuries among drivers and passengers on mopeds. In 2022, a total of 2’929 accidents involving electric scooters occurred in Italy. Numbers that caused a total of 221 fatalities and 19’462 injuries, with pedestrians also being run over. The role of scooters seems to be decisive in this statistic: accidents (+39.4 %), deaths (+77.8 %) and injuries (+47.4 %) are on the rise (ISTAT, 2021). Only 2 % of the sample analysed recorded non-fatal accidents (ISTAT, 2022). Three main reasons for travel were defined, namely home-work; home-school and home-leisure as per literature.

The questionnaire comprised two sections, the first relating to socio-demographic variables such as gender and age, while the second section related to motivation and frequency of scooter travel over the three periods considered.

From the first section, it emerged that 68 % of the sample consisted of male users and 18 % of female users, while the remaining percentage (4 %) preferred not to provide gender details.

As far as age is concerned, the entire sample was made up of users aged 18-25 (15 %), 26-35 (17 %), 36-44 (49 %), 45-54 (11 %) and finally over 55 (8 %).

With the questionnaires, it desired to observe the purpose of the journeys of the individuals with the e-scooter and the changes in the frequency of these journeys according to the pre-pandemic, pandemic process and post-pandemic period. Three different categories have been determined as the main purpose of the journey. In addition, five different categories have been determined for the frequency of e-scooter preference in trips. The classes that can occur with all these variables are shown in Figure 2 below.

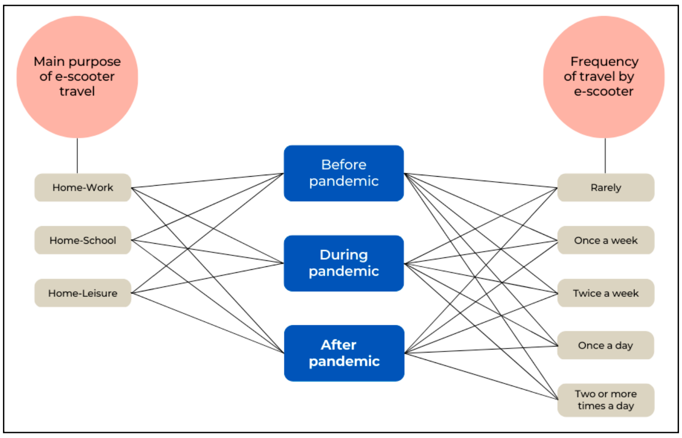

Figure 2. Classes that can be created with existing variables

Although the total number of classes that can occur is 45, the values in some categories are zero in the surveys. For this reason, the number of classes for the current dataset will be less. During the health crisis caused by the pandemic period, there is no user whose main purpose is to travel between home and school. Similarly, there is no number of users whose e-scooter trip frequency is two or more times a day during the health crisis caused by the pandemic period and after the pandemic period. Classes with these categories have not been included in the classification process because there has no data available. The classes in which these categories are included are given in Table 1 below.

Main purpose of e-scooter travel	Time period	Frequency of travel by e-scooter
Home-School	During pandemic	Rarely
		Once a week
		Twice a week
		Once a day
Home-Work		Two or more times a day
Home-Leisure		
Home-School	After pandemic	
Home-Work		
Home-Leisure		
Total number of classes = 10		

Table 1. Classes without any e-scooter users

There are no e-scooter users in the 10 classes given above. Since no one uses e-scooters between home and school due to the closure of schools during the health crisis caused by the pandemic period, there are no users in the 5 classes that match this category. Since there is no person who uses e-scooters two or more times a day during and after the pandemic, there are no users in the classifications that match these categories. For this reason, the number of classes determined for the current dataset is 35. In addition to this situation, it is also possible that the number of elements of some classes is zero as a result of matching between categories.

4. RESULTS AND DISCUSSION

In this study, 35 different classes have been determined for a total of 545 data, and since it would be very difficult to do this classification one by one, the classification process has been carried out with machine learning algorithms. SMO, KNN, and RF algorithms have been used for classification. Since each algorithm examines the existing data set from different aspects, an evaluation has been made on the basis of the results of the most successful algorithm in the analysis.

The evaluation process is based on error and performance criteria. It is very important that these factors obtained from each algorithm are compatible with each other. If the results are not compatible with each other, it can be said that the algorithm failed for the current dataset. The error criteria obtained with each algorithm are shown in Figure 3 below.

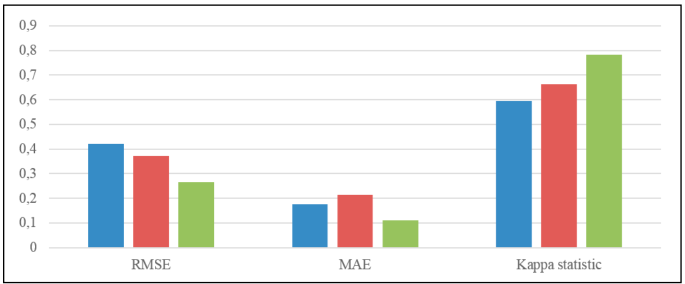

Figure 3. Error criteria obtained from algorithms

When the error criteria obtained from the algorithms are examined, it is seen that the RF algorithm has the highest kappa statistic value and the lowest MAE and RMSE values. On the other hand, while the MAE value of the KNN algorithm is lower than the SMO algorithm, the RMSE value of the SMO algorithm is lower than the KNN algorithm.

This makes it difficult to compare the error values of the two algorithms. However, the fact that the kappa statistic value of the SMO algorithm is higher makes this algorithm a little more prominent.

Another important step in the comparison of these algorithms is the comparison of performance criteria. Studies are based on performance criteria such as accuracy, precision, ROC area, and f-measure. Figure 4 below shows the results obtained with each algorithm.

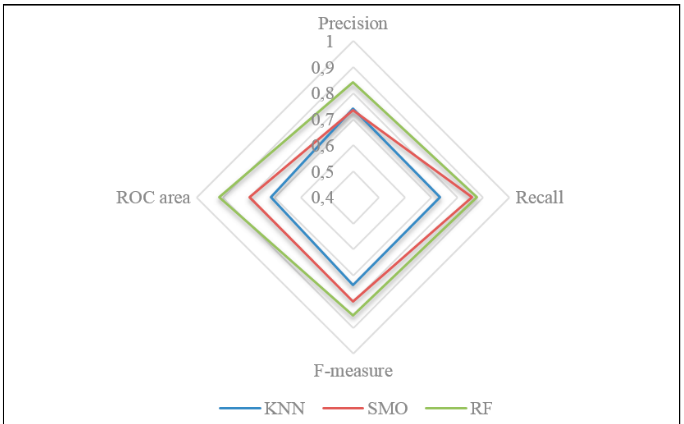

Figure 4. Performance criteria obtained from algorithms

When the results are examined, it is seen that the RF algorithm is more successful than the other two algorithms in terms of both error and performance criteria. It is seen that a single recall value among all criteria gives close results in RF and SMO algorithms.

The SMO algorithm gave more successful results in terms of many criteria compared to the KNN algorithm. As a result of these comparisons, it has decided to use the RF algorithm for the existing dataset. The number of elements belonging to the classification made with the RF algorithm using the previously determined categories is shown in Table 2 below.

	Before Pandemic	During Pandemic	After Pandemic
Home-Work Rarely	5	16	16
Home-Work Once A Week	46	6	105
Home-Work Twice A Week	106	7	106
Home-Work Once A Day	93	1	19
Home-Work Two Or More Times A Day	44	0	0
Home-School Rarely	0	0	1
Home-School Once A Week	3	0	21
Home-School Twice A Week	6	0	21
Home-School Once A Day	2	0	3
Home-School Two Or More Times A Day	1	0	0
Home-Leisure Rarely	2	473	22
Home-Leisure Once A Week	29	30	121
Home-Leisure Twice A Week	85	12	99
Home-Leisure Once A Day	85	0	11
Home-Leisure Two Or More Times A Day	38	0	0

Table 2. Data numbers for each class as a result of the classification made

5. DISCUSSION

As stated in the process of creating the classes, it has been determined that the number of elements in a total of 10 classes has 0. In addition to this situation, when the match between the categories has been provided, in also two different classes the number of elements became zero. When the distribution of the number of members of the classes according to the pandemic process is examined, many issues draw attention. The most striking point is that while the number of individuals who made occasional home-leisure trips with e-scooter before the pandemic was only 2, this number increased to 473 during the health crisis caused by the pandemic period. After the pandemic, this number decreased to 22.

This can show that people are bored at home during the health crisis caused by the pandemic and need rarely travel with an e-scooter. On the other hand, the frequency of travel between home-leisure is higher before and after the pandemic than during the health crisis caused by the pandemic period. This situation reveals that this behaviour is temporary.

Another important point is that during the health crisis caused by the pandemic, it is seen that the frequency of people using e-scooters has decreased in all types of travel. It has also been determined that this situation has a permanent effect after the pandemic. The fact that the individuals surveyed did not use e-scooters one or more times a day after the pandemic supports this situation.

When all these situations are evaluated in general, it has been seen that this situation is a temporary behaviour, although the purpose of most individuals' e-scooter use has changed during the health crisis caused by the pandemic. However, it has been observed that the frequency of e-scooter use has decreased in most individuals during the health crisis caused by the pandemic and this situation has turned into a permanent behaviour.

Another comment to be made on this subject is that the pandemic has reduced the socialization characteristics of people and therefore micro-mobility is also affected by this situation. Considering the results of this study, it is recommended that policy makers conduct a number of campaigns to increase the use of e-scooters by people.

It may be suggested for future researchers to conduct a study that reveals whether there are micro-mobility users before and for what reasons they give up using micro-mobility by conducting various surveys on public transport users of the pandemic process. Maybe it is because the pandemic process is over and people are not worried about their health, so their orientation to public transportation has increased.

These hypotheses are strongly promoted by several studies in recent literature that point to a general trend with regard to Italy and the use of scooters, but also for many European states where the spread of scooters has taken place recently and where there is still little regulation of use.

Our research is in line with other European studies regarding the reasons for choosing the use of electric scooters over other vehicles such as private cars. in fact

The reasons why car users choose a shared e-scooter are less time spent looking for parking and avoiding congestion, but also sustainable behaviour as pointed out by (Weschke, Oostendorp, & Hardinghaus, 2022).

Fear of contagion has kept people away from public transport and car sharing, causing a massive use of private vehicles for travel in various contexts. This is why several national governments and public administrations have focused on enhancing alternative and sustainable means of transport for a new mobility (Useche, Gonzalez-Marin, Faus, & Alonso, 2022).

Various works in the literature show how the lack of legislation and dedicated infrastructures can affect the frequency of use of the aforementioned means of transport.

Therefore, a greater diffusion of road safety education and training programs as well as a diffusion of infrastructure maintenance and the construction of dedicated infrastructures could influence the perception of risk and reduce risky behaviour, road conflicts and the probability of accidents among drivers of electric scooters (della Mura, Failla, Gori, Micucci, & Paganelli, 2022; Hossein Sabbaghian, Llopis-Castelló, & García, 2023).

6. CONCLUSION

The development of technologies and calculation methods makes it possible to analyse in a predictive manner a series of variables that can influence the modal choice in urban areas, such as electric scooters. The study of the trend of use during the last few years characterised by various pandemic phases has made it possible to understand how the user is influenced to use certain forms of transport for the last mile. In recent years, various studies have acquired a range of information and data both through the administration of questionnaires and surveys, but also through the use of GPS tracking of vehicles or smartphones, often resulting in large amounts of data. Among the techniques currently being used to evaluate modal choices are those related to machine learning. This is a subset of artificial intelligence that deals with creating systems that learn or improve performance based on the data they use. This has made it possible to consider frequency variation considering different travel purposes and different time periods. The mobility and transport sector, such as the logistics sector, is promoting a range of research applying the machine learning approach to the improvement of public transport or trucking services, route optimisation, predictive maintenance and driver development. In fact, the present research work analysed trends in attitudes towards e-scooter travel and changes in the frequency of these trips based on the pre-pandemic period, the pandemic process and the post-pandemic period, using different approaches. In the study, classes based on the main purposes of e-scooter users and the frequency of e-scooter use were determined. In the classification made with 3 different algorithms, the RF algorithm showed the most successful performance. In the results obtained from this algorithm, it has been determined that the pandemic affects people's e-scooter usage behaviours. It has been seen that the purpose of using e-scooters for most individuals has changed during the health crisis caused by the pandemic process, but this is a temporary behaviour. However, it has been revealed that the frequency of e-scooter use has decreased in most individuals during the health crisis caused by the pandemic process and this situation has turned into a permanent behaviour. In general, it has been revealed that the pandemic negatively affects micro-mobility. In order to prevent this negative situation, policymakers should work to increase the use of e-scooters. In this way, it can be ensured that people's tendency towards motor vehicles can be prevented. Finally, the results obtained can be a basis for the development of psycho-social and behavioural models useful for analysing the correlation of a series of transport-related variables with social-type variables pre and post variables a series of catastrophic events such as the recent pandemic

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