Hindawi
Journal of Advanced Transportation
Volume 2023, Article ID 1868826, 20 pages
https://doi.org/10.1155/2023/1868826

Research Article

Commuting to College: An Analysis of a Suburban Campus on the Outskirts of Madrid

Mary Luz Mouronte-López and Alberto López

Higher Polytechnic School, Francisco de Vitoria University, Madrid, Spain

Correspondence should be addressed to Mary Luz Mouronte-López; maryluz.mouronte@ufv.es

Received 12 April 2023; Revised 18 July 2023; Accepted 5 September 2023; Published 20 September 2023

Academic Editor: Luigi Dell'Olio

This paper aims to analyse human mobility in a university campus on the outskirts of the Madrid region. Several surveys which were distributed to students for completion during the 2017-2018, 2018-2019, and 2021-2022 courses were examined. Both an exploration of existing transport modes using clustering techniques and a statistical analysis on trip origins, travel times, and distances were performed. Not all municipalities with the highest number of trips were the closest to the university. The clustering analysis identified a lower variability in the use ratio of the transport modes in the 2017-2018 course. The private car, which exhibited a low sharing rate, was the most utilised transport mode. This was followed by public and university transportation. Similarities between the probability distributions of journeys using public and university transports were found. High and moderate correlations between the number of the existing stops and the amount of trips by subway and urban bus were detected. The lowest median values of travel distances corresponded to students, administrative staff, teachers, and researchers who exhibited very similar values. Considering the three analysed academic years as a whole, the most likely travel times were 30–60 minutes. It was detected that a higher gross annual income did not imply higher private car use. Residents in areas with the highest ozone concentrations also exhibited a high use of motorised vehicles. A low familiarisation with car-sharing and car-pooling platforms was also found. Globally, a high level of comfort during the trip was mostly perceived.

1. Introduction

1.1. Importance of Human Mobility in Urban Spaces. Both human and goods mobility are key elements of urban development, determining the urban spaces and the way in which they function. The private car is one of the most widely used modes of transportation for the human displacements European Commission [1], Eurostat [2]. In Spain, according to Ministerio de Fomento [3], the functional dependence of peripheral areas in the city centre has been reduced by the increase in facilities. At the same time, infrastructures and services have increased urban development, resulting in urban sprawl. This has led to (i) an increment in travel distances, (ii) an increase in motorised mobility, (iii) a dispersed mobility demand, which is difficult to satisfy through public transport, and (iv) a raise in congestion, travel times, and environmental pollution.

In 2018, the Regional Transport Consortium of the Madrid community conducted a survey on mobility E. D. M. [4] which was based on telephone and face-to-face interviews. The target population was individuals over 3 years of age residing in the region. 75,208 persons provided data on their mobility, allowing a total of 222,744 trips to be analysed. According to the survey, 27.3% of trips carried out on working days were work-related, 15.7% were study-related, and those caused by both shopping and personal matters accounted for 12% each. 29% of journeys were motivated by other reasons (walking, sport, accompanying another person, leisure, and medical issues). Regarding the distribution of the transportation modes, the most utilised was private cars (39%), followed by walking (34%), public transportation (24.3%), and others (2.7%).

In accordance with the abovementioned, educational services are among those services that produce the greatest number of commuters in the region, which is generally the case in cities Cadima et al. [5]. University students frequently use more diverse modes of transportation than other citizens Paéz and Whalen, Zhou, Whalen et al., Bagdatli and Lpek [6–9]. As a result, some cities have adopted transport plans to improve the overall quality of mobility around university campuses Sgarra et al. [10].

At present, urban transport on offer is undergoing several transformations that will have an impact on the achievement of a more sustainable mobility. Information and Communication Technology helps the implementation of new modes of mobility through so-called "smart mobility," which is expected to facilitate multimodality and increase the use of public transport, as well as improve accessibility in low-demand areas Momentum [11]. The emergence of new mobility paradigms, such as mobility as a service will also have implications on road capacity, traffic evolution, land utilisation, and the urban designs Wong et al. [12].

1.2. Background. Because university students are generators of a large number of commutes, both the traits and factors influencing their mobility have been extensively analysed. Nash and Mitra [13] collected data concerning several universities in Toronto to check patterns in the transportation behaviour of post-secondary students. Two-thirds of the students predominantly travelled on foot, by bicycle, or carried out transitions between transport modes. Obregón Biosca [14] explored the commuting characteristics of students at the Universidad Autónoma de Quétaro, pointing out that the transport choice is mainly related to the trip distance and the individuals' socioeconomic features. Maia et al. [15] suggested that public transport prevails among low-income users in certain locations. Students who can afford higher costs tend to prefer a private vehicle, which is seen as being safer and more comfortable. This is in accordance with Balcombe et al. [16], which mentioned that fares, seven categories of attributes that are decisive in the service quality, incomes, and car-owning impact on the use of public transport. Liu et al. [17] found that student transit riders inhabited in larger households (with more vehicles by resident). Travel time and vehicle ownership per household individual was demonstrated to have a very low influence. Obregón Biosca [14] in line with Nash and Mitra [13] stated that the main cause for using the private car between university students was the lack of alternatives to reach the destination by public transport.

The influence of gender variables on the use of public transport has also been analysed Pérez, Nayum and Nordfjærn [18, 19]. Male students seem to show lower intention to use public transport than female students, as a consequence of the fact that both sexes differ in their orientation towards proenvironmental behaviours Nayum and Nordfjærn, Finisterra do Paço et al., Torgler, [19–21].

Sustainability in universities has also been investigated by Kaplan [22], Balsas [23], Daggett and Gutkowski [24], Gurrutxaga et al. [25], and Cattaneo et al. [26] to obtain reports that provide an overview of the students' commutes in order to achieve reductions in pollution. In particular, the Conference of Rectors of Spanish Universities (CRUE) has, among its aims, evaluated the implementation of good practices in both sustainable mobility and accessibility in Spanish universities, promoting the development of mobility plans Gutíerrez and Jaraíz [27]. Balsero et al. [28] based on the aforementioned mobility survey carried out by the Regional Transport Consortium of the Madrid Community E. D. M. [4] found that the use of public transport was at its majority in six Spanish public universities, with percentages in the range 52%–65%.

Miralles-Guasch and Domene [29] detected that the most important restrictions for changing the travel mode from private car to travel by nonmotorised/public transportation were as follows: (i) lack of appropriate infrastructure, (ii) low level of walking and cycling as a priority mode of travel among the population, and (iii) longer travel times when public transport is utilised.

1.3. Motivation and Objectives of the Research. This research aims to analyse the mobility of individuals attending a private university on the outskirts of Madrid. Student surveys conducted during the 2017-2018, 2018-2019, and 2021-2022 academic years were used. It must be noted that no surveys were prepared for the 2019-2020 and 2020-2021 academic courses because of the COVID-19 pandemic. This investigation focuses on answering the following questions.

(i) What are the most frequently used modes of transport when travelling to university? Is there a pattern of mobility, and has it changed throughout different academic years? What is the perception of trip comfort?

(ii) Which are the general trends in relation to private car use? Are car-sharing and car-pooling platforms known and used?

(iii) What are the statistical characteristics connected with the closest distance to public transport stops? Is there any relationship between the mode of transport used and the aforementioned distance?

The goals to be achieved are derived from the answers to the questions previously exposed.

As a novelty with respect to research described in Section 1.2, various different statistical techniques as well as clustering analysis were used (see Section 2.2). The study was carried out for all profiles of individuals attending campus, as well as for all types of academic studies being pursued. In particular, the following features were examined: (i) Main travel characteristics: most frequent travel origins, used transport modes (various aspects related to sustainability were considered), travel times, and trip-related distances, and also trip comfort. (ii) Supplemental travel information: transportation sharing as well as utilisation of car-sharing and car-pooling platforms.

Specifically, as a novelty with respect to Balsero et al. [28], in addition to the abovementioned, the human mobility examination was conducted in a private university campus. Balsero et al. [28], based on E. D. M. [4], for each individual's profile attending six public universities in 2018, calculated the percentage of used transport modes and compared universities with each other. In order to evaluate the impact caused by COVID pandemic, the information was contrasted with the data obtained from a survey carried out in 2021. The authors also examined information such as the number of trips, the trip times, and schedules.

2. Materials and Methods

2.1. Sample Selection: Design of Surveys—Collected Data. In this research, the target for the surveys was students, teachers, researchers, and people working in administrative services. Undergraduate and graduate level students as well as those taking professional training courses were considered. All surveys were sent to participants through the academic services of the university. For the 2017-2018 and 2018-2019 courses, paper surveys were used, while for the 2021-2022 questionnaire, a Microsoft Form was utilised.

The procedure used for the estimation of the ideal sample selection and the obtained results have been included in the supplementary material document (Section S1.1, Table S1).

The information collected through the surveys was as follows.

(i) Respondent's profile, which includes data concerning the role he/she plays at the university (researchers and teachers, administrative staff, or students), studies pursued (in the case of the student role), which comprises undergraduate, postgraduate, and advanced vocational training, as well as training at School of Haute Cuisine Le Cordon Bleu.

(ii) Data related to the journey, which are trip origin (zip code, community), day of the week and time in which the journey happens, priority transportation mode (public or university transportation, private car or motorcycle, bicycle, and walking). Travel schedules are also monitored (day of the week, morning, and afternoon), distances and trip times (less than 15 minutes, between 15 and 30 minutes, between 30 and 60 minutes, and more than 60 minutes). Moreover, if the journey is by private car, the motorisation and number of companions is recorded (0, 1, 2, 3, 4, 5, or more than 5 persons). If the trip is by motorcycle, motorbike motorisation is noted. Additionally, we registered information on the comfort of the journey, if it is not comfortable, reasons for discomfort (time, distance, traffic, public transport, insufficient parking, and others).

(iii) Data on the use of car-sharing and car-pooling platforms. However, there were some differences in the questions asked in the surveys between the three academic years.

(iv) For 2021-2022 survey, the transportation mode, travel duration, and trip distances should be indicated at every stage of the journey. For the 2017-2018 and 2018-2019 surveys, this information is referred to the full travel itinerary.

(v) Surveys for the 2017-2018 and 2018-2019 courses allowed students to indicate more than one option for the used transport mode (public or university transportation, private car or motorcycle, bicycle, and walking). In the 2021-2022 survey, it was only possible to indicate one transportation mode for each trip step. If applicable, the public bus line used in each stage should also be described.

(vi) Regarding vehicle motorisation, in the 2017-2018 and 2018-2019 courses, it took the following values: gasoline, diesel, hybrid, and electric. In the 2021-2022 course, more detail on typologies of car motorisation could be derived from the results of the survey, which were diesel, pure electric, gasoline, liquefied petroleum gas (LPG), plug-in hybrid, nonplug-in hybrid, or unknown.

Because of the abovementioned, in order to be able to compare the surveys with each other, a data migration procedure was performed.

All used questions in this work can be found in the supplementary material document (Section S1.2 and Section S1.3).

2.2. Overview of Used Methods. In this section, all utilised procedures in this research are explained. The software resources that were required for the implementation of the methods have been briefly described in the supplementary material document (see Section S2).

2.2.1. Analysis of Principal Travel Attributes. In this Section, the used methods for the study of the main trip characteristics are explained (see Section 1.3).

(1) Study of Journey Origins. Most of the people working or studying at the university lived in the Madrid community, which consisted of 179 municipalities. One of them is Madrid city, which is administratively divided into 21 districts. There are 135 postcodes in the Madrid community. For the Madrid community, bar plots showing the number of individuals coming from the 10 most frequent municipalities and postcodes were calculated. We also plotted a histogram representing the number of commuters by postcode. In addition, a map showing the number of individuals by postcode going to the university was displayed.

(2) Study of Used Transport Modes. For the 2017-2018 and 2018-2019 academic courses, each individual could be characterised by a vector $v_{\mathrm{ind}j}$ which represented the ratio of the use of each transport mode over the total number of utilised modes for one individual j. $v_{\mathrm{ind}j}$ is a vector of six elements, where each element (i) symbolises one of the possible transport types: $i = 1$: public transport, $i = 2$: university transport, $i = 3$: private car, $i = 4$: private motorcycle, $i = 5$: bike, and $i = 6$: walking.

$$\overrightarrow{v_{\text{ind}j}} = \left(v_{\text{ind}j1} \ldots v_{\text{ind}j6}\right) = \left(v_{\text{ind}ji}\right), \quad \forall i = 1 \ldots 6, \tag{1}$$

where j can vary from 1 to NR, symbolising NR, the number of respondents.

For instance, an individual (ind$j$) who uses public transport and the private car would be represented by a vector of the form $v_{\text{ind}j} = (0.5, 0, 0.5, 0, 0, 0, 0, 0)$. For the survey referring to the 2021-2022 course, the usage ratio for each individual was estimated, considering the used transport type in each trip step.

In order to study the variables that describe the usage ratios for each transport type, V_i variable, $\forall i = 1 \ldots 6$, their cumulative probability distributions were computed.

Cumulative distribution function of a random variable X is symbolised by $F(x)$, which is stated as $F(x) = \Pr(X \leq x)$. The cumulative distribution function for a discrete random variable X, $n \leq N$, where N is the number of possible outcomes of X, is defined as follows:

$$F(x) = F\left(x_{n-1}\right) = \sum_{k=1}^{n-1} = P_r\left(X = x_k\right), \quad \forall x \in \left[x_{n-1}, x_n\right]. \tag{2}$$

With the aim of comparing the cumulative probability distributions of the variables (V_i), $\forall i = 1 \ldots 6$, the Kolmogorov–Smirnov test Berrendero [30] was applied Massa [31]. The following hypotheses in conjunction with a significance level (α) equal to 0.05 were considered.

(i) Null hypothesis (H_0): "the samples came from the same distribution"

(ii) Alternative hypothesis (H_a):"the samples came from different distributions"

If a p value < 0.05 was obtained in the test, H_0 would be rejected, and H_a would be taken.

The Kolmogorov–Smirnov test allowed us to know if the transport usage ratios exhibited similar distributions. The analysis was carried out both at the overall university level and by the level of studies.

In addition to all the abovementioned, a clustering analysis of transport usage ratios was also carried out. This is a multivariate technique Cisewski, Rodríguez et al. [32, 33] which assigns observations to groups (called clusters) so that in each cluster the observations, which are characterised by certain attributes, are similar to each other, that is, analogous objects are placed in the same group. However, all groups differ from each other.

In order to detect the existing clusters in the transport usage ratios, the K – Means method Ullman et al. [34] was utilised, considering the obtained $v_{\text{ind}j}$ for all respondents of the surveys. Various indexes for determining the optimal number of clusters were also calculated.

A set of data points D $\{V_{\text{ind}1}, V_{\text{ind}2}, \ldots, V_{\text{indNR}}\}$ was considered, in which $V_{\text{ind}j} = \left\{v_{\text{ind}j1}, v_{\text{ind}j2}, \ldots, v_{\text{ind}jr}\right\}$, symbolised a vector $V_{\text{ind}j}$ in $\subseteq R^r$, and r represented the number of dimensions ($r = 6$). The k – Means method groups the data under analysis into k clusters, as follows Ullman et al. [34].

(i) Each cluster possesses a centroid

(ii) Given k, the k – Means algorithm performs the following operations

 (1) Randomly select k data points (which are the initial seeds), representing the initial centroids.
 (2) Using the Euclidean distance as a metric, associate each data point to the nearest centroid.
 (3) Compute the centroids again utilising all data points present in the current cluster.
 (4) If a convergence criterion is not met, steps 2 and 3 must be repeated. The convergence criteria corresponded to the best estimate of 26 indexes (see Table S20, supplementary material document). The optimal number of clusters was considered to be that value in which the highest number of indexes coincided ("majority rule").

In addition to all the above, for the Madrid community, where most of the people attending the university reside, we analysed whether there was a relationship between the influx at the stops and the mode of transport used on each trip. Both the postcode, which represents the administrative region where people reside, and the geolocation of the public transport stops were known. The former could be obtained from the survey results, and the latter could be easily extracted from the data provided by the Madrid Regional Transport Consortium CRTM [35]. In view of the previously mentioned, in each postcode, it was possible to compute the number of stops as well as the number of individuals that use each transport mode. Consequently, we were able to estimate whether there was a relationship between these two quantities at each step of the journey.

To compute the correlation between the aforementioned magnitudes, it was necessary to know whether they were derived from a normal distribution. If there was normality in the variables, Pearson's method should be applied; otherwise, Spearman's algorithm should be used. The normality of the distributions was tested using the Shapiro–Wilks test.

In addition to previously described, the relationship between the type of used transport and variables such as year weighed gross income by postcode/municipality and air pollution was analysed.

The gross annual income data corresponding to 2020 was used, which was obtained from the National Institute of Statistics [36] and the Tax Agency [37].

It must be noted that Madrid city corresponds to the largest and most populous municipality (604.45 square kilometres and 3,280,782 inhabitants in 2022). For Madrid city, the average gross annual income by person and postcode was considered. For the rest of the municipalities, the average gross annual income by person and municipality was taken. Because information on gross income in 2020 was only available for 56 postcodes (see supplementary material document, Section S2), a common average value was contemplated for the remaining postcodes.

Regarding air pollution, information corresponding to each municipality was utilised. In particular, data related to the presence of ozone gases (the amount of nitrogen monoxide, nitrogen dioxide, suspended particulates, and nitrogen oxides were irrelevant compared to that ozone) during May in 2021 was utilised. This information was provided by the Madrid community administration [38]. In order to analyse the concern of individuals who commute to the university, about the pollution in their municipality, the presence of the aforementioned pollutants in the atmosphere was graphically related to the used transportation mode.

(1) Study of Trip Distances, Trip Times, and Trip Schedules. With respect to the examination of the distance travelled by individuals from the origin to university, from the approximate geolocation (longitude/latitude) corresponding to the place where each individual resides, the distance (d) travelled could be estimated.

The cumulative probability distributions of distances for students, researchers, and teachers, as well as administrative staff were calculated. To summarise the central tendency and variability of each distribution, the statistical quartiles were also computed.

For the calculation of approximate distances from origin (ori) to University (des), the Haversine Method Prasetya et al. [39] was applied, where R symbolises the equatorial earth radius (6,378 kilometres).

$$\begin{aligned}
\Delta\text{lat} &= \text{lat}_{\text{des}} - \text{lat}_{\text{ori}},\\
\Delta\text{long} &= \text{long}_{\text{des}} - \text{long}_{\text{ori}},\\
a &= \sin^2\left(\frac{\Delta\text{lat}}{2}\right) + \cos\left(\text{lat}_{\text{ori}}\right) * \cos\left(\text{lat}_{\text{des}}\right) * \sin^2\left(\frac{\Delta\text{long}}{2}\right),\\
c &= 2 * \text{atan}\left(\frac{\sqrt{a}}{\sqrt{1-a}}\right),\\
d &= R * c.
\end{aligned} \tag{3}$$

The function that best fits each distribution was also identified.

Regarding the exploration of minimal distances to public transport stops according to the trip origin, information about the geolocation of all existing public transport stops in the Madrid community was used. For each individual's profile, the approximate lowest distance to each transport node type from the trip's origin was calculated. The cumulative probability distributions and statistical quartiles were also computed. Additionally, the function that provided the best fit with the aforementioned distributions was also identified.

Similarly to trip distances, travel times from origin to destination were statistically studied. For each academic course, the cumulative probability distributions of the trip journeys from origin to destination were compared through the Kolmogorov–Smirnov test. Additionally, histograms were drawn. The trip schedules to university (percentage of individuals travelling by time range) were also examined.

(2) Study of Trip Comfort. The trip comfort was also examined as well as the main reasons for dissatisfaction. The cumulative probability distribution of this variable was analysed.

2.2.2. Analysis of Supplemental Trip Attributes. In this section, the used methods for the study of the supplementary trip characteristics are explained (see Section 1.3).

Both private car occupancy and usage of car-sharing/carpooling platform variables were checked. Their histograms as well as their main statistical parameters (median, mode, and mean) were studied.

3. Results

3.1. Principal Travel Attributes. In this section, the results corresponding to the analysis of the main trip characteristics are presented (see Section 1.3).

3.1.1. Journey Origins. Figure 1 depicts the number of individuals travelling to university by postcode. The location of the university is marked in red. It can be seen that the municipalities with more people travelling to university are some of the closest, although not all of them.

The postcodes corresponding to Pozuelo de Alarcón, Boadilla del Monte, Universidad, Aravaca, Moncloa, Las Rozas de Madrid, Galapagar, Torrelodones, Chamberí-Rios Rosas, and Collado Villalba were among the most usual postcodes in the three academic years. Alcorcón, Boadilla del Monte, Majadahonda, Pozuelo de Alarcón, and Madrid were the most recurring municipalities (see supplementary material document, Section S2. Figures S1 and S2, show the 10 most frequent postcodes and municipalities).

3.1.2. Used Transport Modes. For the 2017-2018, 2018-2019, and 2021-2022 academic courses, as well as for all individual profiles and all levels of study, a higher use of the private vehicle over public and university transport was identified (see Tables 1 and 2). An exception was found for the vocational training studies, in which the utilisation of public transport was more frequent.

In 2017-2018 and 2018-2019, per academic year, the percentage of trips by car were 51.23% and 49.96%. The proportion of trips by public transport was 45.69% and

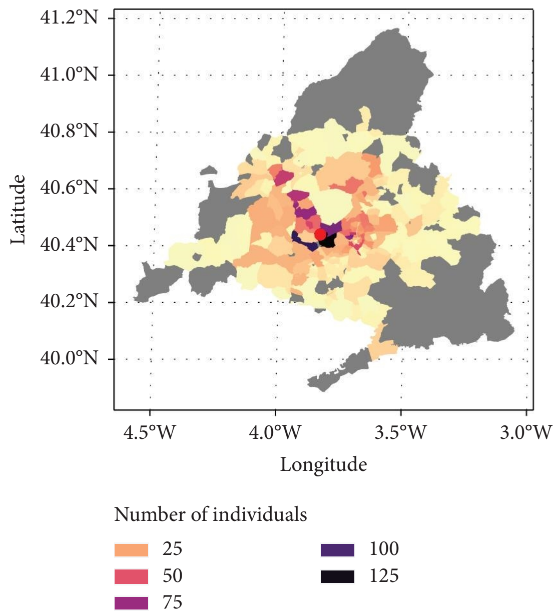


Figure 1: For the Madrid community, individuals travelling to university by postcode in 2021-2022 course. Some information retrieved from CRTM [35] was used for the construction of the map.

Table 1: The percentage of the use of each transport type for each academic course.

Transport type	2017-2018		2018-2019	
	Filled (%)	No filled (%)	Filled (%)	No filled (%)
PT	45.69	54.31	44.35	55.65
UT	44.64	55.36	42.58	57.42
CAR	51.23	48.77	49.96	50.04
M	2.05	97.95	2.13	97.87
BI	0.63	99.37	0.87	99.13
W	4.01	95.99	3.95	96.05

PT: public transport, UT: university transport, CAR: private car, M: motorcycle, BI: bike, W: walking.

44.35%. The percentage of journeys by university transport was 44.64% and 42.58%. With respect to the 2021-2022, per academic year, in the first trip stage, the most recurrent used transportation modes were, in order, car 46.03% and walking 24.43% and 17.45%. In the second step, the most widely used mode of transportation was public transport with 24.34% of trips.

For the 2021-2022 course, histograms of the mode of transport used both at each stage of the journey and by postcode (in stages 1 and 2) have been described in the supplementary material document (Figures S3–S5). Tables showing data on the percentage of use of transport modes by individual's profile (Tables S2–S10 in addition to Tables S11 and S12) have also been included.

Also, for the 2021-2022 course, regarding trip step 1, Figure 2 depicts by postcode, the number of individuals that used each transport mode by postcode. In Figure 3, for trip step 2, similar information is displayed.

In 2021-2022, it was possible to identify some of the most frequently used public bus lines. They were the following five: 561-A (Aluche neighbourhood in Latina district, Las Rozas municipality), 561-B (Pozuelo municipality, Las Rozas municipality), 565 (Boadilla municipality, Pozuelo municipality), 561 (Aluche neighbourhood in Latina district, Las Rozas municipality), and 659 (Moncloa district, Majadahonda municipality). All these lines are managed by the company AVANZA [40]. The university transport was the following buses: Alcorcón-University, Aluche-University, University-MSI Motor and Sport Institute, and Plaza Castilla-University.

Regarding travel stages, 34.62% of persons performed two steps in their journey. 22.03% and 5.28% of the people carried out steps 3 and 4, respectively. And only 1.78% and 0.25% of the people make journeys with steps 5 and 6. It must be noted that various individuals did not consider walking to the car as the first step of the trip.

For all analysed courses, the percentage of use of each type of car motorisation, which was calculated over the total number of car trips could be obtained (see Tables 3 and 4). As previously indicated (see Section 2.1), in the survey corresponding to 2021-2022, more motorisation typologies could be chosen by respondents.

Tables 3 and 4 depict a slight reduction in the percentage of diesel and gasoline cars as well as a small increase in the percentage of hybrid and electric cars during the analysed academic years.

Regarding the usage ratio of transport modes, in 2017-2018 and 2018-2019, in line with the results of Kolmogorov–Smirnov test (p value > 0.05), similarities existed between the probability distributions of public and university transports, as well as between the displacements by motorcycle and bike. No similarities between the aforementioned distributions were detected in the 2021-2022 course (see Table 5).

In the analysis by educational level, for undergraduate and graduate students, the similarity was detected between public and university transport in 2017-2018, as well as between bike, motorcycle, and walking in both 2017-2018 and 2018-2019. For undergraduate students, analogies were found between bike and motorcycle transportation in 2021-2022. Graduate students exhibited similarities between walking, bike, motorcycle, as well as public and university transport.

Tables displaying information on the transport utilisation ratios and the obtained p value in the Kolmogorov–Smirnov test by individual's profile can be found in the supplementary material document (see Tables S13–S18).

With respect to clustering analysis, for the 2017-2018 course, according to "the majority rule," the optimal number of clusters was 2. This magnitude was 3 for the 2018-2019 and 2021-2022 courses. For the 2017-2018 and 2018-2019 courses, in cluster 1, the highest means, medians, and modes corresponded to public (0.42, 0.56, and 0.42) and university transport (0.42, 0.27, and 0.42). In cluster 2, the highest values were associated with trips by car (0.98, 0.89, and 0.98). For the 2021-2022 course, cluster 1 and 2 exhibited the highest values for car (0.99, 1, and 1) and public transport (0.77, 1, and 1) journeys, respectively. Cluster 3 showed the largest values for public transport trips (0.50, 0.50, and 0.33).

Table 2: The percentage of the use of each transport type, in each step, for 2021-2022 course.

Transport type	Step 1 (%)	Step 2 (%)	Step 3 (%)	Step 4 (%)	Step 5 (%)	Step 6 (%)
PT	17.45	24.34	8.18	1.45	0.25	0.03
UT	7.48	7.17	11.20	3.14	0.28	0.15
CAR	46.03	2.25	0.30	0.09	0.03	0
M	0.71	0.18	0	0	0	0
BI	0.09	0.06	0	0	0	0
W	24.43	0.62	2.34	1.11	0.52	0.06
Unfilled	3.82	65.38	77.97	94.22	98.92	99.75

PT: public transport, UT: university transport, CAR: private car, M: motorcycle, BI: bike, W: walking.

It is noteworthy that in all courses, there was a cluster of individuals who used mainly private cars (modes took the values 0.98 and 1). According to the results, in the 2018-2019 course, there was a cluster of persons that relevantly utilised university transport (mode is equal to 0.89). In 2021-2022 a cluster that exhibited a high use of public transport existed (mode took a value equal to 1).

A table depicting the number of obtained clusters according to the indicated metrics in Section 2.2.1 can be found in the supplementary material document (Table S19). The document also describes tables showing mean, median, mode, and standard deviation in each cluster (Tables S20–S22 as well as Table S23).

For the 2021-2022 course, the dependence of the chosen transport mode on the number of available public transport stops was also analysed. The Shapiro–Wilks test was applied in order to check the normality of the variables. None of the variables derived from a normal distribution, since the p value was lower than 0.5 in all cases (see supplementary material document, Tables S24 and S25). Since, there was no normality in the aforementioned variables, the Spearman's algorithm was applied to calculate the correlations. A high correlation existed between the displacements by subway and the numbers of subway stops. However, a low association was found in the movements by commuter trains and Madrid's urban buses as well as by light subway (see Table 6). It is noteworthy that the journeys by interurban bus exhibited a low negative correlation with the number of stops. A moderate association was found in the displacements by urban bus.

In 2021-2022, the relationships between the type of transport used and the variables of economic income and air pollution were also examined. In Figure 4, which displays the transport mode as a function of the weighted gross income in step 1 (A) and 2 (B), it can be seen that a higher gross annual income do not seem to imply higher private vehicle use. Regarding pollution, Figure 5 depicts the transport mode as a function of ozone concentration in steps 1 and 2. It can be observed that even in those areas with the highest ozone concentrations, individuals were travelling to the university by private car and motorcycle.

3.1.3. Trip Distances, Travel Times, and Schedules. With regards to trip times, it can be observed that the most likely travel times are 15–30 minutes and 30–60 minutes for the 2017-2018 and 2018-2019 academic courses. In the 2021-2022 academic course, the most likely duration of trips are 30–60 minutes and ≥ 1 hour. With respect to schedules, most individuals stay in the university during the morning in all analysed academic courses. In the 2017-2018 course, 36.80% and 27.15% of students stay in the university during the morning or afternoon, respectively. 29.51% is there during the morning and afternoon. In the 2018-2019 course, these percentages were 43.09%, 16.82%, and 33.85%. With respect to the 2021-2022 course, these features were 72.12%, 19.35%, and 4.12%.

Figures showing the cumulative probability distributions and histograms related to trip times for the 2017-2018, 2018-2019, and 2021-2022 courses have been described in the supplementary material document (Figures S9 and S10). For the 2021-2022 course, the document also includes histograms of duration in each step of the journey (Figure S11) in addition to histograms of the schedules in which individuals stay in the university (Figure S8).

Regarding travel distances, Table 7 depicts, for each individual's profile, the statistical quartiles that correspond to the trip distance. The lowest median values corresponded to students. Administrative staff, teachers, and researchers exhibited very similar values.

Tables 8 and 9 display the functions that provide the best fit with the cumulative probability distribution of the aforementioned distance. Students as well as researchers and teachers were characterised by an accumulative probability distribution which could be conveniently described by a Pareto 2 function. In contrast, figures which correspond to the administrative staff were symbolised by a Box–Cox power exponential function (see Table 8). A Box–Cox power exponential function can be defined as follows Rigby, et al., Stasinopoulos and Rigby, R-gamlss, Stasinopoulos et al. [41–44]:

$$f(y|\mu,\sigma,\nu,\tau) = y^{\nu-1}\frac{\tau\exp\left[-1/2|z/c|^{\tau}\right]}{\mu^{\nu}\sigma c 2^{1+1/\tau}\Gamma(1/\tau)}, \tag{4}$$

where $c = [2^{(-2/\tau)}\Gamma(1/\tau)/\Gamma(3/\tau)]^{0.5}$, where if $\nu \neq 0$, then $z = [(y/\mu)]^{\nu} - 1]/(\nu\sigma)$ else $z = \log(y/\mu)/\sigma$, for $y > 0$, $\mu > 0$, $\sigma > 0$, $\nu = (-\inf, +\inf)$, and $\tau > 0$.

Analogous information which referred to the distribution of closer distances to public transportation stops is described in Tables 10–12. In the Madrid community, the most dispersed networks correspond to interurban bus and urban bus networks. This is in addition to the commuter trains network. Therefore, these networks are those that exhibit the greatest reach (see Figure 6).

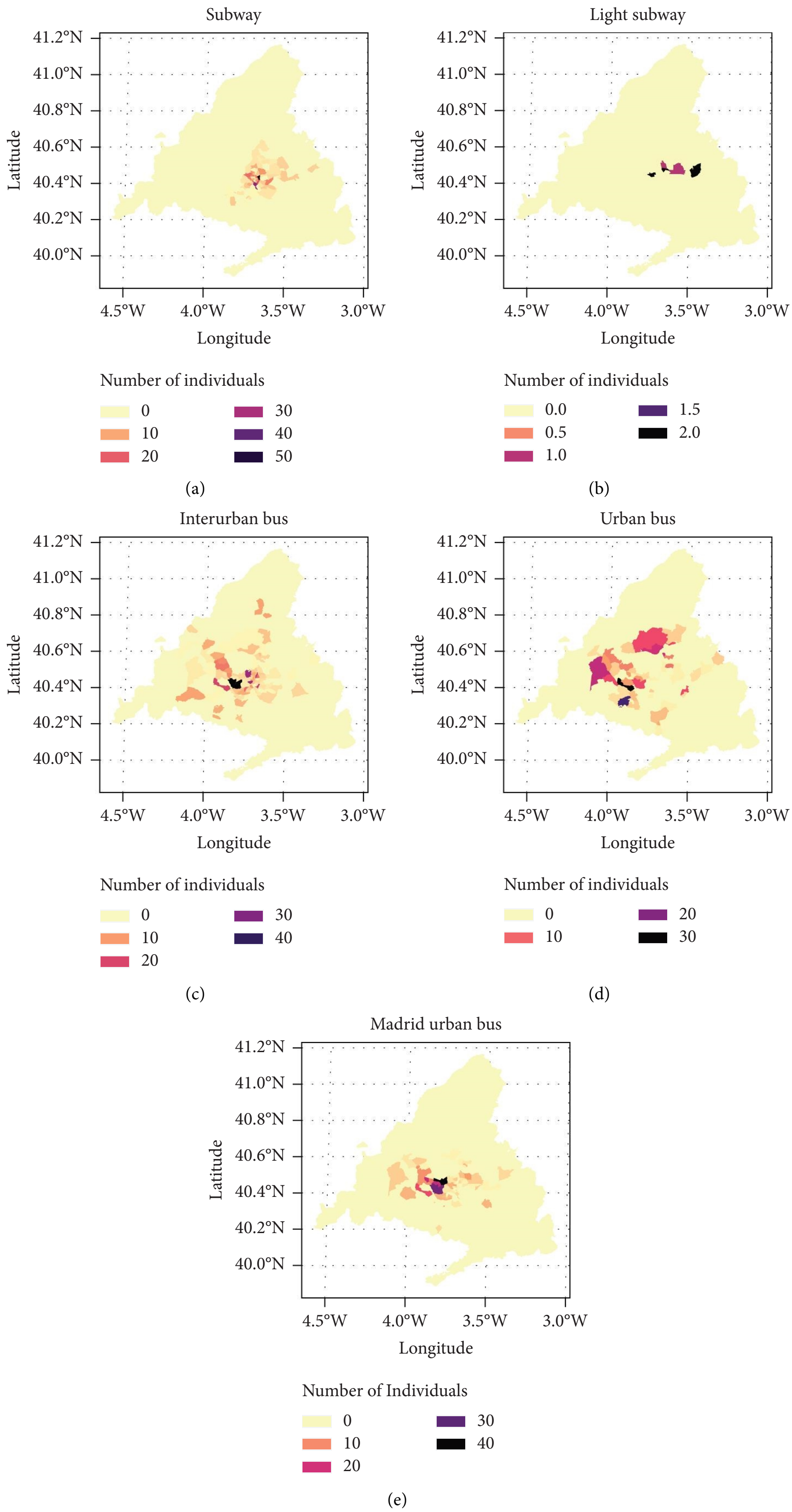


Figure 2: For the Madrid community, for the 2021-2022 course, the number of individuals who used public transport in step 1. Some information retrieved from CRTM [35] was used for the construction of the map. (a) Subway. (b) Light subway. (c) Interurban bus. (d) Urban bus. (e) Madrid urban bus.

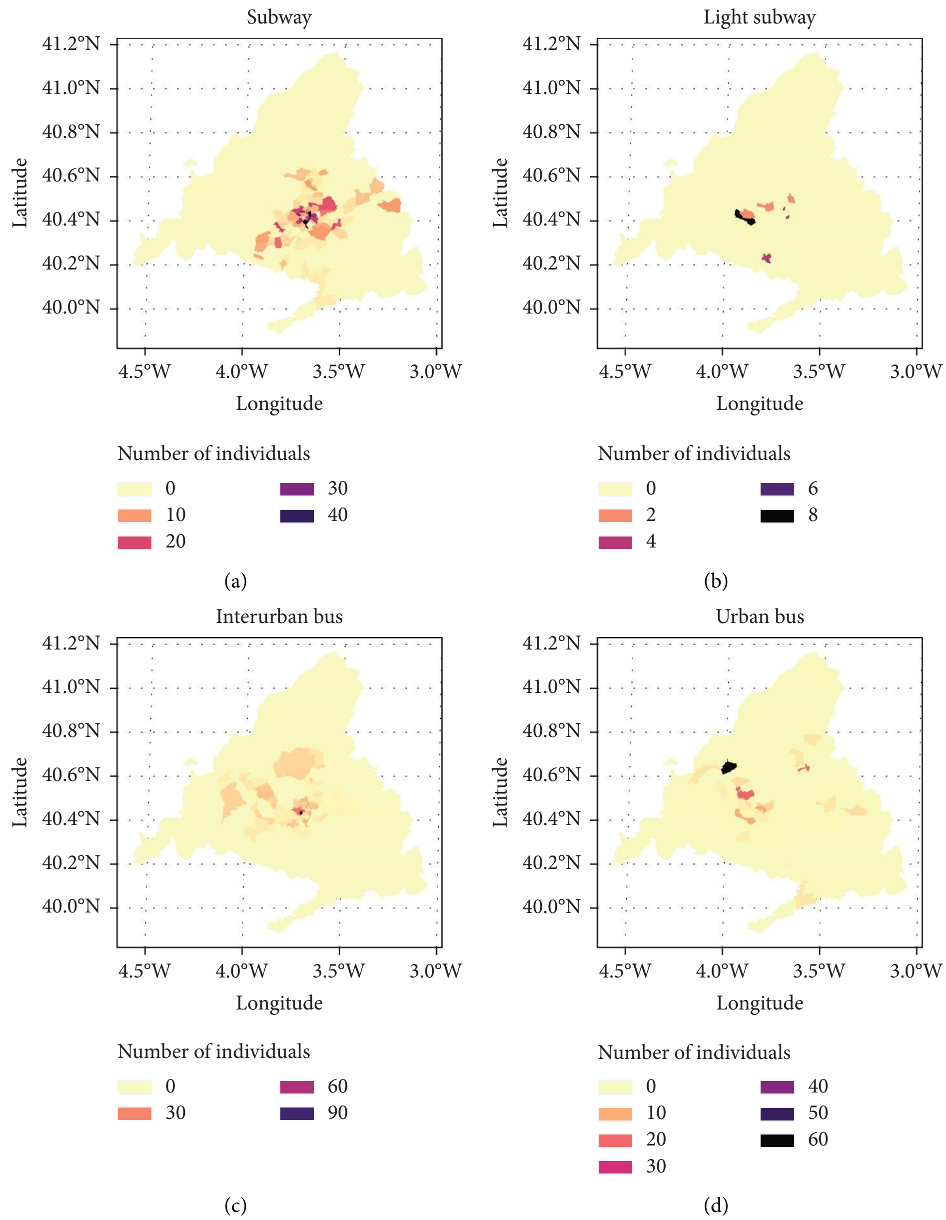
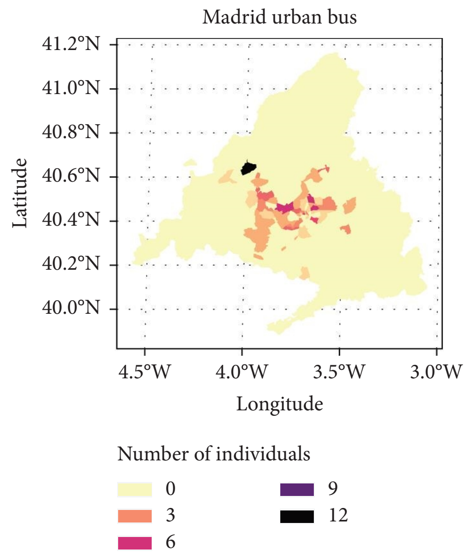


Figure 3: Continued.



(e)

Figure 3: For the Madrid community, for the 2021-2022 course, the number of individuals who used public transport in step 2. No individual used the commuter trains for trip step 2. Some information retrieved from CRTM [35] was used for the construction of the map. (a) Subway. (b) Light subway. (c) Interurban bus. (d) Urban bus. (e) Madrid urban bus.

As can be observed in Table 11, for administrative staff as well as teachers and researchers, the cumulative probability distributions followed a type 2 Pareto function.

A Pareto distribution type 2 is defined as follows Rigby, et al., Stasinopoulos and Rigby, R-gamlss [41–43]:

$$f(y|\mu,\sigma) = \frac{1}{\sigma}\mu^{1/\sigma}(y+\mu)^{-1/\sigma+1}, \tag{5}$$

where $y \geqslant 0, \mu > 0$ and $\sigma > 0$.

However, that corresponded to students who could be properly fitted by a Box-Cox-Cole-Green-Orig function.

The probability distribution function of a Box–Cox Cole and Green distribution is defined as follows Rigby & Stasinopoulos, Rigby and Stasinopoulos, Stasinopoulos et al., Hastie and Tibshirani, Stasinopoulos & Rigby [42, 43, 45–48]:

$$f(y|\mu,\sigma,\nu) = \frac{1}{\sqrt{2*PI*\sigma}}\frac{y^{\nu-1}}{\mu^{\nu}}\exp\left(-\frac{z^2}{2}\right), \tag{6}$$

where if $\nu \neq 0$, then

$$\left\{\frac{(y/\mu)^{\nu}-1}{\nu\sigma}\right\}, \tag{7}$$

else

$$z = \frac{\log(y/\mu)}{\sigma}, \tag{8}$$

where $y > 0$, $\mu > 0$, $\sigma > 0$, and $\nu = (-\infty, +\infty)$.

For students, researchers, and teachers, the closest public transport stops correspond to the subway and light subway. By contrast, for administrative staff the nearest stops are those associated with the commuter trains (see Table 10).

3.1.4. Trip Comfort. Most individuals thought the trip was comfortable in all analysed courses (50.17%, 55.93%, and 61.49% in the 2017-2018, 2018-2019, and 2021-2022 academic courses, respectively). The most important causes of discomfort in the 2017-2018 course were time, distance, and traffic (51.83%, 46.33%, and 39.39%, respectively). In the 2018-2019 course, these figures varied slightly, displaying time and distance (46.78% and 37.89%, respectively). Time (29.36%) was the main issue in the 2021-2022 course.

Figures showing the number of individuals by cause of discomfort (time, distance, traffic problems, transportation, insufficient parking, and other reasons) have been incorporated in the supplementary material document (Figure S12). It must be noted that not all persons answered the questions related to travel comfort.

3.2. Supplemental Trip Attributes. In this section, the results corresponding to the analysis of the supplementary trip characteristics are presented (see Section 1.3).

For all analysed courses, the highest probability of the private car occupancy variable corresponded to vehicles occupied by only one person.

Figures displaying the histograms and the cumulative probability distributions corresponding to the number of people in private cars have been included in the supplementary material document (Figures S6 and S7). Table 13 depicts the main statistical parameters referred to the aforementioned variable.

Regarding the usage of car-sharing and car-pooling platforms, most persons knew the car-sharing platforms but did not use them in all academic courses (in 2021-2022, 69.60% persons had knowledge of the car-sharing platforms but did not utilise them, while 20.58% individuals had never heard of them. These features were 61.69% and 9.92% and 61.69% and 14.10% in 2017-2018 and 2018-2019, respectively). Figure displaying the histograms related to car-sharing and car-pooling platforms for all analysed courses

Table 3: The percentage of the use of each type of car for the 2017-2018 and 2018-2019 courses.

Year	2017-2018	2018-2019
Type of motorisation	Percentage (%)	
Diesel	51.62	53.22
Gasoline	44.92	40.55
Hybrid	2.84	4.97
Electric	0.55	1.26

Table 4: The percentage of car motorisation types for the 2021-2022 course.

Type of motorisation	Percentage (%)
Diesel	49.68
Gasoline	38.14
Nonplug-in hybrid	5.83
Pure electric	2.18
Plug-in hybrid	1.60
LPG	1.47
Unknown	1.09

Table 5: Similarity between cumulative probability distributions of transport utilisation ratios.

	PT	UT	CAR	M	BI	W
2017-2018 survey						
PT	1	0.74	0	0	0	0
UT	0.74	1	0	0	0	0.82
CAR	0	0	1	0	0	0
M	0	0	0	1	0.81	0.43
BI	0	0	0	0.81	1	0.02
W	0	0	0	0.43	0.02	1
2021-2022 survey						
PT	1	0	0	0	0	0
UT	0	1	0	0	0	0
CAR	0	0	1	0	0	0
M	0	0	0	1	1	0
BI	0	0	0	1	1	0
W	0	0	0	0	0	1
2018-2019 survey						
PT	1	0.82	0	0	0	0
UT	1	1	0	0	0	0
CAR	0	0	1	0	0	0
M	0	0	0	1	0.94	0.78
BI	0	0	0	0.94	1	0.17
W	0	0	0	0.78	0.17	1

PT: public transport, UT: university transport, CAR: private car, M: motorcycle, BI: bike, W: walking.

have been included in the supplementary material document (Figure S13).

4. Discussion

4.1. Principal Travel Attributes. In this section, the results referring to the main trip characteristics are discussed (see Section 1.3).

4.1.1. Journey Origins. As has been previously commented on, not all postcodes with the highest number of students are the closest to the university. This is in line with Studygram [49] which explains that the most relevant factors that determine the choice of university are the academic majors, the academic quality, and the university reputation; the accreditation, the cost of tuition and living, as well as the available scholarships are significant factors. Finally, the university location, the level of career opportunity and success, the faculty members' helpfulness as well as the campus environment are among the main causes [49]. Word-of-mouth marketing has been recognised as one of the most important drivers of university choice, particularly recommendations from friends and family Elliott and Healy, Spearman et al. [50, 51]. Various pieces of research describe that working and nonworking students value the factors that motivate them differently when selecting a university. Students who were not working estimated that social media, word-of-mouth, and school presentations strongly influence their decision. Working students are more influenced by outdoor advertising Spearman et al. [51].

4.1.2. Used Transport Modes. The results show that the car was the most used transportation mode, followed by the public and university transport in the campus. Bike, motorcycle, and walking were much less utilised. The slight increment detected in the number of hybrid and electric cars was probably due to government subsidies, existing tax credits, and rebates for the purchase of these types of vehicles.

A greater use of private vehicles by students compared to other modes of transportation was also detected in certain universities around the world Zhou, Ribeiro et al. [52, 53].

With respect to the dependence of the chosen transport mode on the number of available public transport stop, the correlation analysis show that the used transport mode in step 1 may depend more on other factors such as the used mode in the next stage of the journey than on the number of existing public transport stops.

The journeys to university are usually multimodal, as a completed journey often requires two or three modes of transportation (one of them walking). Transfers in the public transport system, in addition to impact on the use of certain routes and destinations, have been demonstrated to cause disruption in the trip experience and diminish public transport's competitiveness with the private car, which provides door-to-door service Guo and Wilson [54]. The utilisation on-demand services with shared use to reach the university from certain origins (postcodes) could be an alternative option to the private car utilisation.

The results describe a higher variability in the use of transport modes during the latter two courses (since they exhibited a higher number of clusters). Each cluster consists of individuals who are relatively homogeneous in terms of modes of transportation to commute to the university. A characterisation of individuals on the basis of clusters of transport usage ratios could be useful for the determination of appropriate policies and new strategies related to human

Table 6: Correlation between number of stops by postcode and number of individuals by transport mode in trip steps 1 and 2 for the Madrid community in the 2021-2022 course.

Transport type	Correlation step 1	Correlation step 2
Subway	0.70	0.6
Madrid urban bus	0.2	0.4
Urban bus	0.3	0.3
Interurban bus	−0.2	−0.2
Light subway	0.2	—
Commuter trains	0.2	—

A hyphen means some of the values to be analysed are constant, which results in a standard deviation equal to zero and, consequently, the correlation function returns an NA (not available) value.

mobility in the campus. Meetings could be held with some of the individuals located in each cluster, in order to find out in detail what motivates them to use each transport mode, as well as to explore the positive and negative perceptions of each.

In order to reduce the use of private cars by university employees and students and thus achieve a more sustainable conduct, a variety of the following factors could be taken into consideration.

According to Schwartz [55], ecological conducts are the results of the activation of personal norms that manifest sentiments of moral obligation to either execute or refrain from performing actions. If a desire to execute an ecological behaviour exists, the individual has a favourable attitude towards it. However, if the person faces external (psychosocial and contextual causes) or internal (personality causes) barriers, an attitude-behaviour gap is formed. Consequently, there is a decrease in the rate of compliance with these ecological conducts even when the intention is to carry them out. In particular, [56] the awareness of consequences, the attribution of responsibility, the personal norms, the behavioural intention, as well as the habit of using the private car, and the access to it, impact on the final fulfilment of the aforementioned conducts. To modify the habit of using the private car, it is required that universities implement both structural and psychological actions Setiawan et al. [56]. The interventions must include principles and techniques both to eliminate the custom and to increase the responsibility towards the negative impact of the utilisation of the private car Setiawan et al. [56].

As was previously commented on, cycling, motorcycling, and walking have low usage rates in the university campus analysed in this research. With regard to walking, some pieces of research showed that in Europe, individuals aged 17-18 years old commute by walking up to 2 kilometres D'Haese et al., Van Dyck [57, 58]. It is clear that the further away one lives from a commuting location, the less likely one is to commute actively. However, the walkable distance from home to the study location seems to depend on other factors as well (urban planning and cultural perceptions) Rousseeuw, Rodríguez-Rodríguez et al. [59, 60]. In accordance with this, Djurhuus et al. [61] detected, based on a Danish National Health Survey, that there was no significant association between the distance to the nearest bus stop and an active commute.

Regarding cycling, Spanish Statistics National Institute, INE. [62], provides information related to European Health Survey corresponding to 2020, which describes the use of the bicycle to get around (for population aged 15 and over). Features show that 92.19% of the Spanish population did not use the bicycle, indicating a general absence of cycling culture. Research points out that several cities exhibit rather relevant statistics related to cycling among students, which has been achieved because of several factors Pogačar et al. [63]: (i) universities are within walking distance of public transport stations, (ii) detailed planning and relevant investments were made over many years to promote sustainability, (iii) special policies towards students have been implemented (limiting the use of parking), (iv) propitius topography, (v) good quality infrastructure, and (vi) support for students in cycling activities.

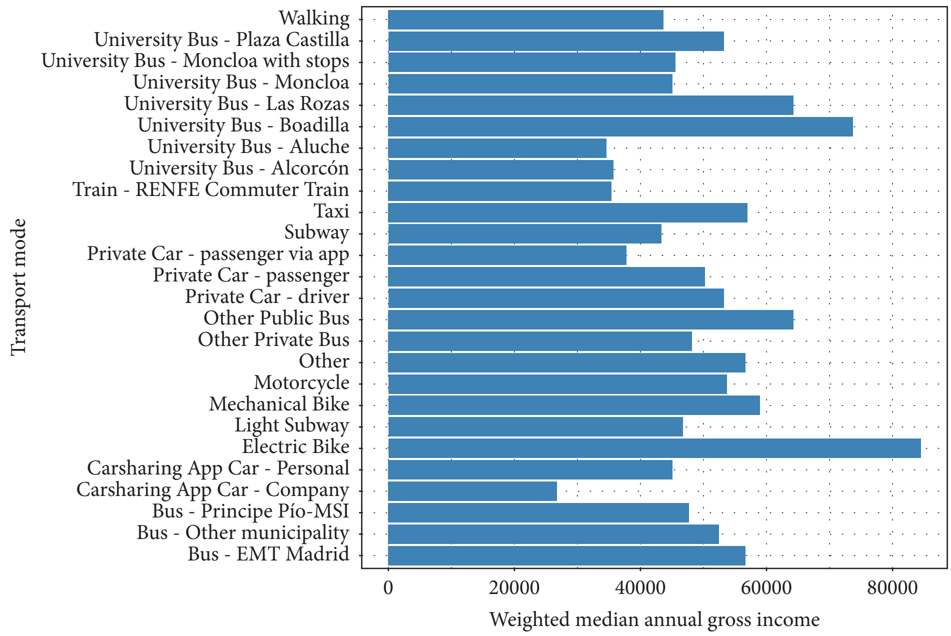
In the analysed university campus in this research, in order to achieve the use of a more sustainable mode of transport, in addition to considering some of the actions listed above, which were proposed in Pogačar et al. [63], a reorganisation of land use, prioritising cyclists, pedestrians, and university transport over private cars could be carried out.

The result show that a higher gross annual income does not imply higher private vehicle use, which is in line with Aluko [64], who found, focusing on a higher institution's teaching staff in Ekiti State (Nigeria) that the majority of workers (81.8%) used private cars, while only a small percentage (9.1%) used public transport services. This was apparent despite the lower cost of public transport compared to private vehicles (around 16%). An analysis carried out by the University of the West of England in 2019 Chatterjee et al. [65] points out that economic circumstances and spatial context appear to account for much of the variation in bus use.

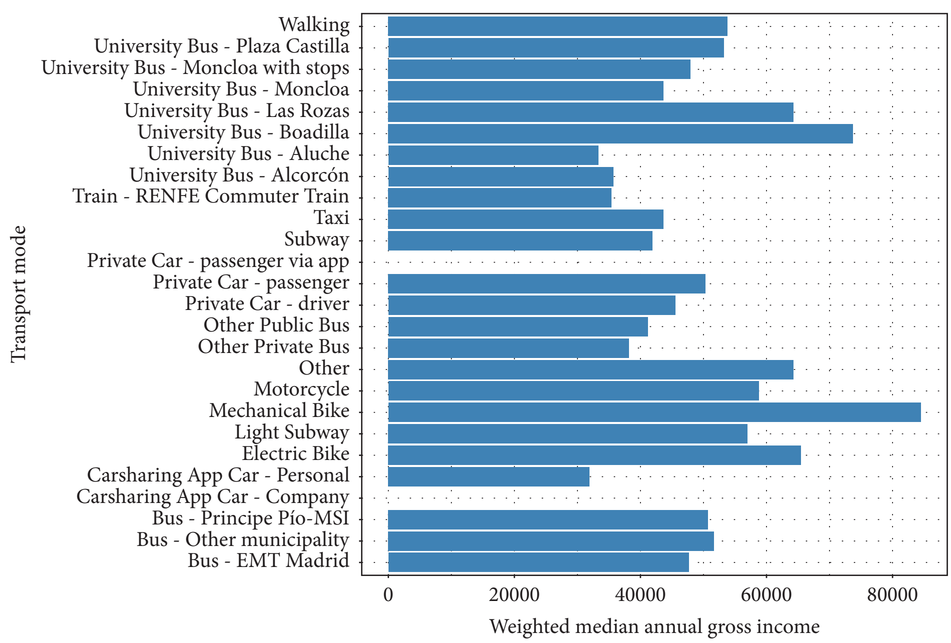
With respect to the air quality, and the used transport mode, the results show that environmental policies and awareness-raising in the zones with the highest ozone concentration should be carried out by public administrations. This is because, in those areas, individuals continued to use motorised vehicles.

4.1.3. Trip Distances, Travel Times, and Schedules. Certain variability was observed with regard to the most likely travel times during the three analysed academic years. However, if the three academic courses are taken as a whole, the most probable travel time was 30–60 minutes. This figure is higher than the one found for the Madrid community, where the average journey time is 25 minutes E. D. M. [4].

With respect to travel distances, as we have mentioned, the results show that the cumulative probability distributions of the travel distances, could be appropriately characterised by Pareto 2 and Box–Cox power exponential functions. Various existing pieces of research showed that the probability of an individual's movement with distance Δd, denoted by $P(\Delta d)$, decreases with an increase in Δd. In



(a)



(b)

Figure 4: Transport mode as a function of weighted gross income in Steps 1 and 2. EMT refers to Empresa Municipal de Transportes (municipal transportation company), which manages the urban buses in Madrid. The Renfe-Operator, E. P. E., is the main passenger and freight rail transport company in Spain. Commuter trains are managed by this firm.

addition it is suggested that $P(\Delta d)$ can be fitted by different statistical distributions such as power law, exponential law, or exponentially truncated power law, among others Liu et al. [66].

The medians of the distances to reach the university campus were similar to the average travel distances in the European Union but higher than the existing ones in the Madrid Community. In Europe, according to the report "Transport New Mobility Patterns Study: insights into passenger mobility and urban logistics", which was conducted from March to August 2021 by the European Commission [67], displays the average length of travel distance per person and per day in urban trips does not exceed 14 km. According to E. D. M. [4], in the Madrid community, the average travel distance in mechanised modes was 8.8 km.

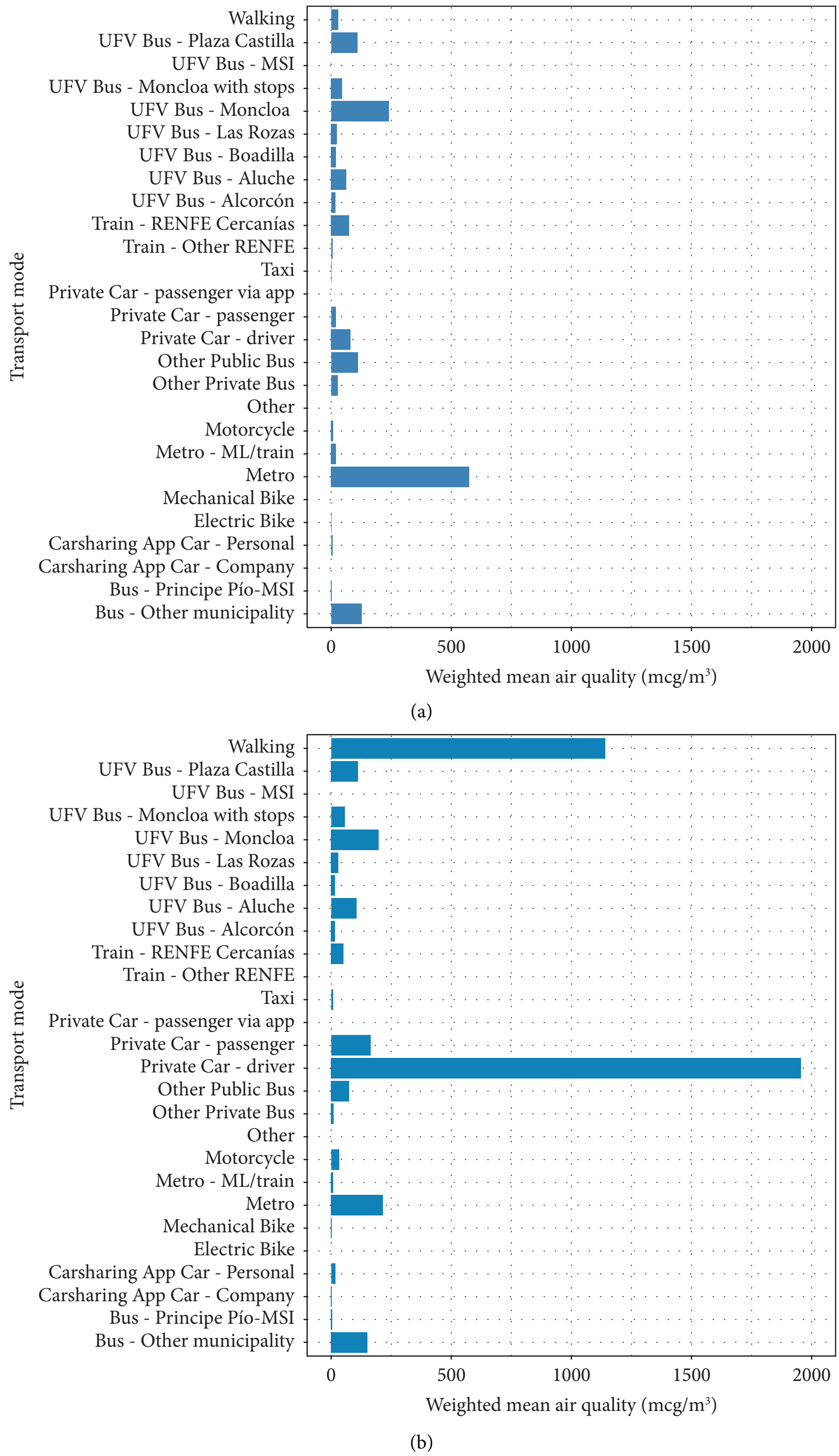


FIGURE 5: Transport mode as a function of ozone concentration in step 1 and 2. EMT refers to Empresa Municipal de Transportes (municipal transportation company), which manages the urban buses in Madrid.

Table 7: Statistical quartiles of the travelled distance in kilometres from origin to university for each individual's profile.

Individual's profile	25%	50%	75%	100%
Teachers and researchers	10.65	13.44	16.83	383.06
Administrative staff	10.48	13.37	16.22	49.05
Students	10.60	12.88	15.93	408.52

Table 8: Function that provides the best fit with the cumulative probability distribution of the approximate distance in kilometres from the origin to the university for each individual's profile.

Individual's profile	Function with the best fit	DOF	RDOF	GD	AIC	SBC
Teachers and researchers	Pareto type 2	2	6	−289.29	−285.29	−285.13
Administrative staff	BCPE, Box–Cox power exponential	4	6	65.21	73.21	74.42
Students	Pareto type 2	2	7	−36.53	−32.53	−32.14

RDOF: residual degrees of freedom for the fit. DOF: degrees of freedom for the fit. GD: global deviance.

Table 9: Parameters corresponding to the function that provides the best fit with cumulative probability distribution of the approximate distance from the origin to the university in kilometres for each individual's profile.

Individual's profile	Parameters
Teachers and researchers	$\mu = -36.81$ and $\sigma = 2.66$
Administrative staff	$\mu = 64.82, \sigma = 2.14, \nu = -0.69,$ and $\tau = 5.80$
Students	$\mu = -37.75$ and $\sigma = 3.34$

Table 10: Statistical quartiles of approximate distance to public transport nearest stop from the origin in kilometres for each individual's profile.

Individual's profile	PT	25%	50%	75%	100%
Teachers and researchers	Interurban bus	0.16	0.42	0.84	262.31
	Subway	0.02	0.12	0.37	347.12
	Commuter trains	3.15	5.15	7.92	364.63
	Light subway	0.24	0.13	0.37	347.12
	Bus	0.84	1.41	2.23	344.48
Administrative staff	Interurban bus	0.23	0.47	1.14	43.57
	Subway	2.79	5.14	7.38	36.94
	Commuter trains	0.07	0.13	0.22	39.42
	Light subway	0.86	1.34	2.00	9.75
	Bus	0.18	0.18	0.87	4.13
Students	Interurban bus	0.23	52.70	10.17	365.93
	Subway	0.20	0.40	0.83	411.13
	Commuter trains	3.10	5.21	6.74	406.95
	Light subway	0.06	0.11	0.18	405.72
	Bus	0.79	1.37	2.18	371.74

4.1.4. Trip Comfort. According to the obtained results, the opinion on trip comfort was mostly positive in all academic courses.

In order to improve the travel comfort (time and distance), several transformations, which could be implemented in the public transport commute, were identified. Modifications, which should be carried out in a coordinated dialogue between the Madrid City Council, the Regional Transport Consortium, and the University, are as follows: (i) Improving the design of currently available public transport routes, even if they require individuals to make more transfers. (ii) Establishment of public transport frequency in coordination with university schedules. (iii) Improvement of time, reducing the period in which users walk between and wait for transfers. (iv) Actions to make better use of travel time could be performed, for example, by providing passengers with electronic devices (computers, laptops, and tablets) including office and entertainment applications to be used during the trip.

4.2. Supplemental Trip Attributes. In this section, the results referring to the supplementary trip characteristics are discussed (see Section 1.3).

As we have mentioned, during the journey, the most probable number of persons in a private car was 1. This is in line with information related to the European Union where the private car is the dominant mode of transport with less than 2 persons on average per car. In particular, for the population aged 15–84, the mean occupancy rate for a passenger car used in urban trips is in the range [1.20, 1.90] individuals, with a minimum value of 1.17 in Italy (population aged 15–80) and a maximum value of 1.87 in Romania Eurostat [68].

With regards to the use of car-sharing and car-pooling platforms, for all academic courses, a non-negligible percentage of individuals said they were not familiar with these types of platforms. It must be noted that many universities Genikomsakis et al., Reyes et al. [69–71] have among the objectives of their mobility policy to reduce the number of vehicles on their campuses as well as to fight against the utilisation of the car alone. This has led them to implement car-sharing and car-pooling strategies. However, various factors must be considered for carrying out these actions successfully. Certain research points out that saving money

Table 11: Functions that provide the best fit with the probability cumulative distribution of the approximate distance to public transport nearest stop from the origin for each individual's profile.

Individual's profile	Function with the best fit	DOF	RDOF	GD	AIC	SBC
Teachers and researchers	Pareto type 2	2	12	−777.86	−773.86	−772.58
Administrative staff	Pareto type 2	2	7	−34.69	−30.69	−30.29
Students	BCCGo, Box-Cox-Cole-Green-Orig	3	−2	−53.80	−47.80	−53.80

RDOF: residual degrees of freedom for the fit. DOF: degrees of freedom for the fit. GD: global deviance.

Table 12: Parameters of the functions that provide the best fit with the probability cumulative distribution of the approximate distance to public transport nearest stop from the origin for each individual's profile.

Individual's profile	Parameters
Teachers and researchers	$\mu = -36.09$ and $\sigma = 1.71$
Administrative staff	$\mu = -45.27$ and $\sigma = -3.39$
Students	$\mu = -4.93e - 13, \sigma = -28.20,$ and $\nu = 1.42$

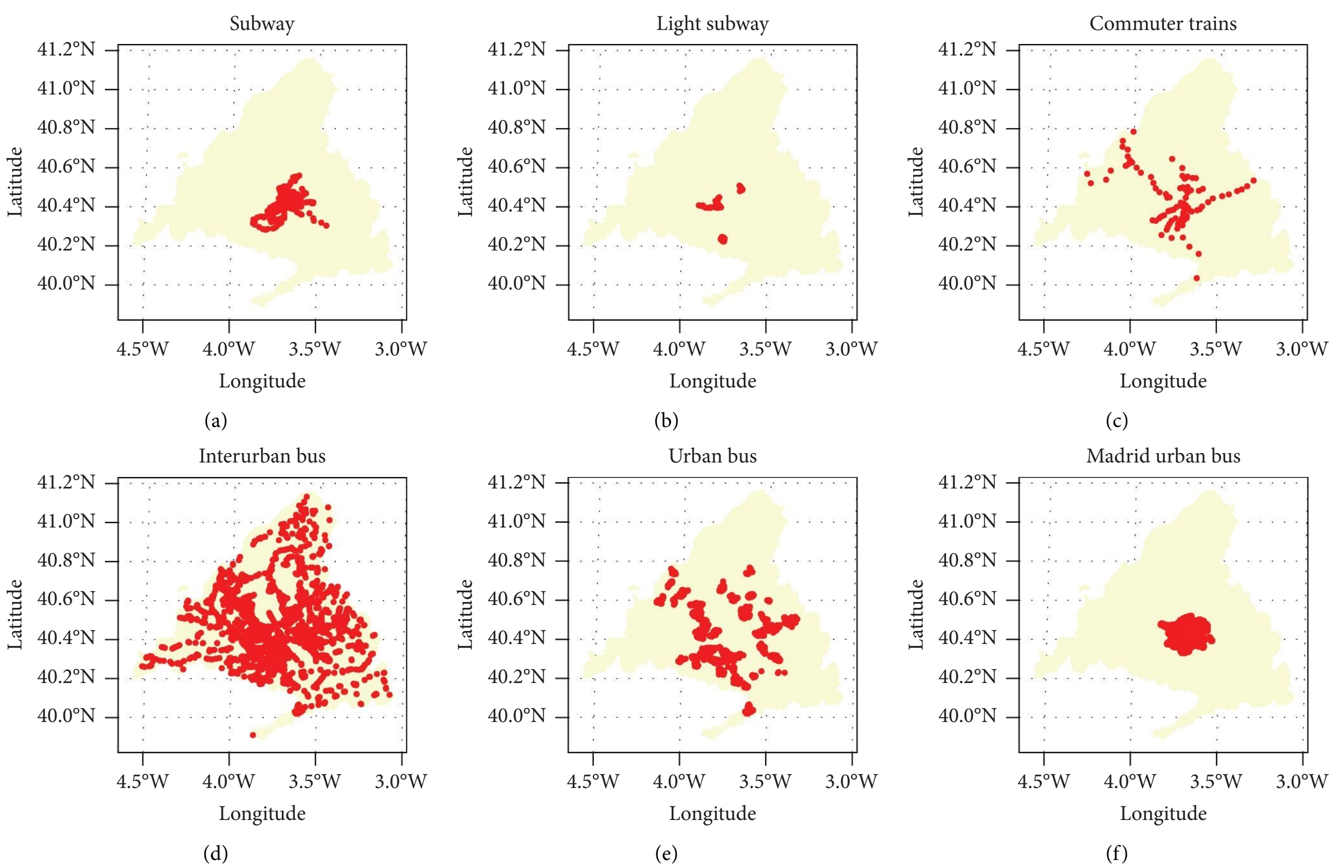


Figure 6: For the Madrid Community, in each postcode, for 2021-2022 course, location of stops by transport type. Information retrieved from CRTM [35] was used for the construction of the map. (a) Subway. (b) Light subway. (c) Commuter trains. (d) Interurban bus. (e) Urban bus. (f) Madrid urban bus.

is one of the principal causes for utilising car-pooling Bento et al., Ciasullo et al. [72, 73]. Other relevant reasons are environmental efficiency, comfort, traffic, socialisation, and curiosity. Among the main causes of deterrence are the privacy protection and the perception of the danger of travelling with strangers Ciasullo et al. [73]. Also, an analysis conducted in Lahore city Muhammad and Ali [74] showed that certain factors had a relevant influence on the individual's decision to adopt a car-pooling alternative. These included, commuters' marital status, education level, daily

Table 13: Main statistical parameters corresponding to the number of individuals in private car for each course.

Course	Median	Media	Standard deviation	Mode
2017-2018	1	1.83	1.16	1
2018-2019	1	1.82	1.17	1
2021-2022	1	1.40	0.77	1

trip distance, the mode of travel usually used, household income, car ownership, and the possession of a driving licence. Additionally, both the reason for the trip and the number of people with whom the vehicle was shared also had an important impact.

With respect to car-sharing, users often perceive it as an innovation to be tested. Car-sharing provides a flexible alternative that meets diverse transportation needs while reducing the negative impact of private vehicle ownership Duziak, Ramos et al. [75, 76] which was carried out a survey taking as sample 1,519 users and 3,695 nonusers of car-sharing. The survey included 36 questions regarding attitudes towards car-sharing, the environment, political orientation, personal norms, frequency of utilisation of transport modes as well as transport mode choice for different trip purposes. The authors found five clusters, including both users and nonusers of car-sharing whose members differed regarding both psychological and behavioural aspects. They were multimode and low environmentalism (user mobility type 1), car-focused ambivalent (user mobility type 2), active public transport green (user mobility type 3), car-focused low-green (nonuser mobility type 4), and multimode and high environmentalism (nonuser mobility type 5).

5. Conclusions and Future Research

The conclusions obtained for each of the objectives are detailed below.

What are the most frequently used modes of travel to university? Is there a pattern of mobility, and has this pattern changed from academic year to academic year? What are perceptions on journey comfort?

Globally, the most frequently used mode of transportation for commuting to university was the private car. In the analysis by level of studies, only vocational training students used cars and public transport in a similar percentage. According to cluster analysis, some differences in the patterns of mobility existed among the three academic years. Two clusters were detected for 2017-2018 and for 2018-2019 courses. By contrast, for the 2021-2022 course, three clusters were identified. In all three courses, a cluster of individuals who mainly used private cars existed, while in 2018-2019, a cluster of persons that relevantly utilised the university transport was found. In 2021-2022, a cluster that exhibited a high use of public transport existed.

In order to establish actions to encourage public transport or that which is offered by the university, focus groups and qualitative surveys should be conducted. This would allow us to obtain more detail on the causes that motivate, in general, a greater use of the private car.

With respect to the trip's comfort, the opinion was mostly positive. Time, distance, and traffic were identified as the main inconveniences.

What are the characteristics of private car usage? Are digital car-sharing and car-pooling platforms known and used?

As indicated by the statistical metrics used, the highest probability corresponded to vehicles occupied by only one person. More than 60% of individuals said they were aware of car-sharing/car-pooling platforms but had never used them. Works aimed at increasing the awareness of individuals about the benefits of car-pooling should be carried out.

A slight increase in the use of hybrid and electric cars in detriment of gasoline and diesel cars was also detected.

What are the statistical characteristics of distances and journey duration to the university?

With respect to approximate distances to the university, different cumulative probability distributions were detected among the different profiles of individuals. Students, as well as researchers and teachers, were appropriately characterised by a Pareto 2 function. In contrast, the cumulative probability distribution associated with the administrative staff followed a Box–Cox power exponential function.

The lowest median of the approximate distance to the university corresponded to students. Researchers and teachers, as well as administrative staff exhibited very similar values. This suggests that distance to the university is among many of the factors that may influence the choice of university.

Travel times changed over the analysed academic years, probably because of the higher academic offers. In 2021-2022, the most probable trip times were higher or equal to 30 minutes.

What are the statistical characteristics of the closest distance an individual can travel in order to reach a public transport stop? Is there any relationship between the mode of transport used and this distance?

For administrative staff as well as teachers and researchers, the cumulative probability distributions of the aforementioned approximate distance followed a type 2 Pareto function. By contrast for students, the distribution could be appropriately represented by a Box-Cox-Cole-Green-Orig function.

For students, researchers, and teachers, the lower median of the distance to the nearest public transport stops corresponded to subway and light subway. Nevertheless, for administrative staff, the lower closest stops were associated with the commuter trains.

The chosen transport mode for one trip step seems to depend more on the mode of transport to be utilised in the next trip stages and, to a lesser extent, on the number of stops in the postcode of the origin of the journey.

Additionally, no direct relationship was detected between income level and private car use.

Both private vehicle and motorcycle use was associated with higher ozone pollution. In these areas, specific awareness-raising actions with an important focus on sustainability should be carried out.

This work could be continued by analysing the relationships between the used mode of transport and other socioeconomic factors not examined in this research. These could be, among others, the level of education of the students' parents, or the place of birth of the commuters.

An exploration of the perceptions of trip comfort based on the analysis of the text completed by the respondents in future surveys could be carried out. Various methods concerning sentiment analysis, which is a procedure that mechanically identifies attitudes, opinions, or emotions from text, could be used Balakrishnan, Janda et al., Kaur et al. [77–79].

Carbon footprint could also be evaluated for commuting to university based on ISO 14069 standards, even distinguishing by individual profiles. ISO 14069 I. S. O. [80] provides guidance on the quantification and reporting of greenhouse gas emissions for organisations.

Data Availability

The anonymous data used to support the findings of this study are available from the corresponding author upon request.

Disclosure

This research was carried out as a result of the Project: PASCAL, a study of commuting to Francisco de Vitoria University, which was granted in the internal call for research projects in 2022 at the aforementioned university.

Conflicts of Interest

The authors declare that they have no conflicts of interest regarding the publication of this paper.

Acknowledgments

The authors express gratitude to María Latasa Pérez, Carlota Gómez Rodríguez, and Javier Fuentes Lastau for their assistance in the statistical calculations and the maps construction. This research was partially supported by Telefónica Chair and AVANZA Chair at Francisco de Vitoria University.

Supplementary Materials

Supplementary material includes the following: (i) Sample selection: calculation of ideal size (Table S1 and Section S1.1). (ii) Surveys of the 2017-2018, 2018-2019, and 2021-2022 academic years (Sections S1.2 and S1.3). (iii) Postcodes (S2). (iv) In-house software. (v) Figures displaying the number of individuals coming from the 10 most frequent municipalities and postcodes (Figures S1 and S2). (vi) Histograms of used transport mode quad (Figures S3–S5). (vii) Tables showing the percentage of use of transport modes by individual's profile (Tables S2–S12). (viii) Tables displaying information on the transport utilisation ratios and the obtained p value in the Kolmogorov–Smirnov test by individual's profile (Tables S13–S18). (ix) Tables including results corresponding to the clustering analysis (Table S19). (x) Tables showing mean, median, and mode as well as standard deviation in each cluster (Tables S20–S23). (xi) Figures analysing the number of persons in private car during the journey (Figures S6 and S7). (xii) Figure displaying the schedules in which individuals stay in the university (Figure S8). (xiii) Figures displaying the trip times (Figures S9–S11). (xiv) Figure depicting results of the analysis of the trip comfort (Figure S12). (xv) Figure showing the usage of mobile platforms (Figure S13). (xvi) Tables analysing the dependence of the chosen transport mode on the number of available public transport stops (Tables S24 and S25). (*Supplementary Materials*)

References

[1] European Comission, "Urban data platform plus. the future of cities," 2020, https://urban.jrc.ec.europa.eu/thefutureofcities/mobility#the-chapter.

[2] Eurostat, "Eurostat statiscal explained. passenger mobility statistics," 2022, https://ec.europa.eu/eurostat/statistics-explained/index.php?title=Passenger_mobility_statistics.

[3] M. de Fomento, "Ministerio de fomento. el tansporte urbano y metropolitano en españa," 2010, https://www.fomento.gob.es/az.bbmf.web/documentacion/pdf/r16823.pdf.

[4] Edm, "Encuesta de movilidad 2018. cómo te mueves?," 2018, https://datos.crtm.es/documents/edm2018viajes/about.

[5] C. Cadima, C. Silva, and P. Pinho, "Changing student mobility behaviour under financial crisis: lessons from a case study in the Oporto University," *Journal of Transport Geography*, vol. 87, Article ID 102800, 2020.

[6] A. Páez and K. Whalen, "Enjoyment of commute: a comparison of different transportation modes," *Transportation Research Part A: Policy and Practice*, vol. 44, no. 7, pp. 537–549, 2010.

[7] J. Zhou, "Sustainable commute in a car-dominant city: factors affecting alternative mode choices among university students," *Transportation Research Part A: Policy and Practice*, vol. 46, no. 7, pp. 1013–1029, 2012.

[8] K. E. Whalen, A. Páez, and J. A. Carrasco, "Mode choice of university students commuting to schooland the role of active travel," *Journal of Transport Geography*, vol. 31, pp. 132–142, 2013.

[9] M. E. C. Bagdatli and F. Ipek, "Transport mode preferences of university students in post-COVID-19 pandemic," *Transport Policy*, vol. 118, pp. 20–32, 2022.

[10] V. Sgarra, E. Meta, M. R. Saporito, L. Persia, and D. S. Usami, "Improving sustainable mobility in university campuses: the case study of Sapienza University," *Transportation Research Procedia*, vol. 60, pp. 108–115, 2022.

[11] Momentum, "New mobility options and urban mobility. challenges and opportunities for transport planning and modelling," 2020, https://h2020-momentum.eu/wp-content/uploads/2020/01/MOMENTUM-D2.1-New-Mobility-Options-and-Urban-Mobility.pdf.

[12] Y. Wong, D. Hensher, and C. Mulley, "Emerging transport technologies and the modal efficiency framework: a case for mobility as a service," in *Proceedings of the 15th International Conference Series on Competition and Ownership in Land Passenger Transport (Thredbo 15)*, Stockholm, Sweden, August, 2017.

[13] S. Nash and R. Mitra, “University students’ transportation patterns, and the role of neighbourhood types and attitudes,” *Journal of Transport Geography*, vol. 76, pp. 200–211, 2019.
[14] S. A. Obregón Biosca, “College student mobility in emerging countries: case study on Universidad Autónoma de Querétaro, México,” *Transportation Research Interdisciplinary Perspectives*, vol. 6, Article ID 100155, 2020.
[15] A. G. Maia, C. Carvalho, L. Venâncio, and E. Dini, “The motives behind transport mode choice: a study with university students in Brazil,” *Ambiente and Sociedade*, vol. 23, 2020.
[16] R. Balcombe, R. Mackett, N. Paulley et al., “The demand for public transport: a practical guide,” Transportation Research Laboratory Report (TRL593), Transportation Research Laboratory, London, UK, 2004.
[17] C. Liu, E. Bardaka, and E. Paschalidis, “Sustainable transport choices in public transit access: travel behavior differences between university students and other young adults,” *International Journal of Sustainable Transportation*, vol. 17, no. 6, pp. 679–695, 2022.
[18] K. J. Perez, “Estudio de los factores por género que determinan el uso del transporte público entre los estudiantes universitarios en el distrito metropolitano de quito,” 2020, https://bibdigital.epn.edu.ec/handle/15000/20883?locale=de.
[19] A. Nayum and T. Nordfjærn, “Predictors of public transport use among university students during the winter: a mimic modelling approach,” *Travel Behaviour and Society*, vol. 22, pp. 236–243, 2021.
[20] A. Finisterra do Paço, M. Barata Raposo, and W. Filho, “Identifying the green consumer: a segmentation study,” *Journal of Targeting, Measurement and Analysis for Marketing*, vol. 17, no. 1, pp. 17–25, 2009.
[21] B. Torgler, M. A. García, and A. Macintyre, “Differences in preferences towards the environment: the impact of a gender, age and parental effect,” *FEEM Working Paper No. 18*, 2008.
[22] D. H. Kaplan, “Transportation sustainability on a university campus,” *International Journal of Sustainability in Higher Education*, vol. 16, no. 2, pp. 173–186, 2015.
[23] C. J. L. Balsas, “Sustainable transportation planning on college campuses,” *Transport Policy*, vol. 10, no. 1, pp. 35–49, 2003.
[24] J. Daggett and R. Gutkowski, “University transportation survey: transportation in university communities,” *Transportation Research Record*, vol. 1835, no. 1, pp. 42–49, 2003.
[25] I. Gurrutxaga, M. Iturrate, U. Oses, and H. Garcia, “Analysis of the modal choice of transport at the case of university: case of university of the Basque country of san sebastian,” *Transportation Research Part A: Policy and Practice*, vol. 105, pp. 233–244, 2017.
[26] M. Cattaneo, P. Malighetti, C. Morlotti, and S. Paleari, “Students’ mobility attitudes and sustainable transport mode choice,” *International Journal of Sustainability in Higher Education*, vol. 19, no. 5, pp. 942–962, 2018.
[27] J. A. Gutiérrez and F. J. Jaraíz, “Plan de movilidad sostenible de la universidad de extremadura diagnóstico de la movilidad en los campus,” 2017, https://www.unex.es/organizacion/servicios-universitarios/servicios/servicio_prevencion.
[28] L. Balsero, K. Lamarty, and A. Monzón, “Mobility to university campuses in the Madrid Community: diagnosis and bases for a sustainability strategy,” *Transportation Research Procedia*, vol. 58, pp. 511–518, 2021.
[29] C. Miralles-Guasch and E. Domene, “Sustainable transport challenges in a suburban university: the case of the Autonomous University of Barcelona,” *Transport Policy*, vol. 17, no. 6, pp. 454–463, 2010.
[30] J. R. Berrendero, “Kolmogorov-smirnov test,” Departamento de Matemáticas. Universidad Autónoma de Madrid, Madrid, Spain, 2004.
[31] S. Massa, *Lecture 13: Kolmogorov Smirnov Test and Power*, Department of Statistics, University of Oxford, Oxford, UK, 2016.
[32] J. Cisewski, *Multivariate Analysis, Clustering, and Classification*, Yale University, New Haven, CT, USA, 2017, https://astrostatistics.psu.edu/su17/17Lectures/stat_learning2017.pdf.
[33] M. Z. Rodríguez, C. H. Comin, D. Casanova et al., “Clustering algorithms: a comparative approach,” *PLoS One*, vol. 14, no. 1, Article ID e0210236, 2019.
[34] S. Ullman Ullman, T. Poggio, D. Harari, D. Zysman, and D. Seibert, “9.54 class 13 unsupervised learning clustering,” 2014, http://www.mit.edu/%7E9.54/fall14/slides/Class13.pdf.
[35] Crtm, “Datos abiertos crtm powered by crtm,” 2019, https://data-crtm.opendata.arcgis.com/.
[36] National Institute of Statistics (Ine), “Resultados por municipios, distritos y secciones censales. indicadores de renta media y mediana,” 2020, https://www.ine.es/jaxiT3/Datos.htm.
[37] A. Tax, “Renta bruta y renta disponible inframunicipal tramos de base imponible: total,” 2019, https://sede.agenciatributaria.gob.es/AEAT/Contenidos_Comunes/La_Agencia_Tributaria/Estadisticas/Publicaciones/sites/irpfCodPostal/2019/jrubikf44a5ab7a1e14e3ab549262b8a16cecff3a2b06c2.html.
[38] Madrid Comunity Administration, “Datos abiertos red de calidad del aire. datos del mes en curso,” 2019, https://datos.comunidad.madrid/catalogo/dataset/calidad_aire_datos_mes.
[39] D. A. Prasetya, P. T. Nguyen, R. Faizullin, I. Iswanto, and E. F. Armay, “Resolving the shortest path problem using the haversine algorithm,” *Journal of Critical Reviews*, vol. 7, no. 1, pp. 62–64, 2020.
[40] Avanza, *AVANZA Mobility ADO*, https://www.avanzabus.com/, 2020.
[41] R. A. Rigby, D. M. Stasinopoulos, G. Z. Heller, and F. De Bastiani, *Distributions for Modeling Location, Scale, and Shape: Using GAMLSS in R*, Chapman and Hall/CRC, Boca Raton, FL, USA, 2019.
[42] D. M. Stasinopoulos and R. Rigby, “Generalized additive models for location scale and shape (GAMLSS) in R,” *Journal of Statistical Software*, vol. 23, no. 7, 2007.
[43] R-gamlss, *Package ‘gamlss.Dist’*, 2023,https://cran.r-project.org/web/packages/gamlss.dist/gamlss.dist.pdf.
[44] D. M. Stasinopoulos, R. Rigby, G. Heller, V. Voudouris, and F. De Bastiani, *Flexible Regression and Smoothing: Using GAMLSS in R*, CRC Press, Boca Raton, FL, USA, 2017.
[45] R. A. Rigby and D. M. Stasinopoulos, “Generalized additive models for location, scale and shape,” *Journal of the Royal Statistical Society- Series C: Applied Statistics*, vol. 54, no. 3, pp. 507–554, 2005.
[46] R. A. Rigby and D. M. Stasinopoulos, “Smooth centile curves for skew and kurtotic data modelled using the Box-Cox Power Exponential distribution,” *Statistics in Medicine*, vol. 23, no. 19, pp. 3053–3076, 2004.
[47] M. Stasinopoulos, B. Rigby, V. Voudouris, C. Akantziliotou, M. Enea, and D. Kiose, “Package ‘gamlss’,” 2022, https://cran.r-project.org/web/packages/gamlss/gamlss.pdf.
[48] T. Hastie and R. Tibshirani, “Generalized additive models,” *Statistical Science*, vol. 1, no. 3, pp. 297–310, 1986.
[49] Studygram, “9 factors to consider when choosing a university,” 2020, https://studygram.me/blog/9-factors-to-consider-when-choosing-a-university.

[50] M. Elliott and A. Healy, “Key factors influencing student satisfaction related to recruitment and retention,” *Journal of Marketing for Higher Education*, vol. 10, no. 4, pp. 1–11, 2001.

[51] J. Spearman, S. Ghanayem, and N. Ljepava, “Factors influencing student enrollment and choice of university,” in *Proceedings of the 35th International Business Research Conference*, American University in the Emirates, Dubai, UAE, May 2016.

[52] J. Zhou, “Carsharing on university campus: subsidies, commuter benefits, and their impacts on carsharing,” *Transportation Research Part D: Transport and Environment*, vol. 32, pp. 316–319, 2014.

[53] P. Ribeiro, F. Fonseca, and T. Meireles, “Sustainable mobility patterns to university campuses: evaluation and constraints,” *Case Studies on Transport Policy*, vol. 8, no. 2, pp. 639–647, 2020.

[54] Z. Guo and N. H. M. Wilson, “Assessing the cost of transfer inconvenience in public transport systems: a case study of the London Underground, *Transportation Research Part A: Policy and Practice*,” *Transportation Research Part A: Policy and Practice*, vol. 45, no. 2, pp. 91–104, 2011.

[55] S. H. Schwartz, “Normative influences on altruism,” *Advances in Experimental Social Psychology*, vol. 10, no. C, pp. 221–279, 1977.

[56] R. Setiawan, W. Santosa, and A. Sjafruddin, “Effect of habit and car access on student behavior using cars for traveling to campus,” *Procedia Engineering*, vol. 125, pp. 571–578, 2015.

[57] S. D’Haese, F. De Meester, I. De Bourdeaudhuij, B. Deforche, and G. Cardon, “Criterion distances and environmental correlates of active commuting to school in children,” *International Journal of Behavioral Nutrition and Physical Activity*, vol. 8, no. 1, p. 88, 2011.

[58] D. Van Dyck, I. De Bourdeaudhuij, G. Cardon, and B. Deforche, “Criterion distances and correlates of active transportation to school in Belgian older adolescents,” *International Journal of Behavioral Nutrition and Physical Activity*, vol. 7, no. 1, p. 87, 2010.

[59] P. Rousseeuw, “Silhouettes: a graphical aid to the interpretation and validation of cluster analysis,” *Journal of Computational and Applied Mathematics*, vol. 20, pp. 53–65, 1987.

[60] F. Rodríguez-Rodríguez, O. Pakomio Jara, N. M. Kuthe, M. Herrador-Colmenero, R. Ramírez-Vélez, and P. Chillón, “Influence of distance, area, and cultural context in active commuting: continental and insular children,” *PLoS One*, vol. 14, no. 3, Article ID e0213159, 2019.

[61] S. Djurhuus, H. Hansen, M. Aadahl, and C. Glümer, “The association between access to public transportation and self-reported active commuting,” *International Journal of Environmental Research and Public Health*, vol. 11, no. 12, pp. 12632–12651, 2014.

[62] Ine, “Actividad física. Utilización de la bicicleta para desplazarse según sexo y grupo de edad. Población de 15 y más años,” 2020, https://www.ine.es/jaxiT3/Datos.htm?tpx=48061w.

[63] K. Pogačar, L. Dežan, M. Lamot, and M. Rencelj, “Determinants of bicycle use among student population: exploratory research of social and infrastructure factors,” *Applied System Innovation*, vol. 3, no. 1, p. 6, 2020.

[64] O. O. Aluko, “Commute expenditure characteristics of a higher institution teaching staff in Ekiti State,” *International Journal of Scientific Engineering and Research*, vol. 9, no. 5, 2018.

[65] K. Chatterjee, B. Clark, A. Nguyen et al., “Access to transport and life opportunities,” Department for Transport, 2019, https://assets.publishing.service.gov.uk/government/uploads/system/uploads/attachment_data/file/831766/access_to_transport_report.pdf.

[66] Y. Liu, Z. Sui, C. Kang, and Y. Gao, “Uncovering patterns of inter-urban trip and spatial interaction from social media check-in data,” *PLoS One*, vol. 9, no. 1, Article ID e86026, 2014.

[67] EuropeanComission, “Mobility and transport new mobility patterns study: insights into passenger mobility and urban logistics,” 2022, https://transport.ec.europa.eu/news-events/news/new-mobility-patterns-study-insights-passenger-mobility-and-urban-logistics-2022-12-20_en.

[68] Eurostat, “Passenger mobility statistics eurostat statistics explain,” 2023, https://ec.europa.eu/eurostat/statistics-explained/index.php?title=Passenger_mobility_statistics#Passenger_car_occupancy.

[69] Liege University, “Car-sharing and carpooling,” 2018, https://www.campus.uliege.be/cms/c_9111000/en/car-sharing-and-carpooling.

[70] K. N. Genikomsakis, C. S. Ioakimidis, B. Bocquier, D. Savvidis, and D. Simic, “Electromobility and carsharing/carpooling services at the University of Deusto: a preliminary exploratory survey,” in *Proceedings of the 16th International IEEE Conference on Intelligent Transportation Systems (ITSC 2013)*, pp. 1935–1940, The Hague, Netherlands, October, 2013.

[71] J. A. Reyes, J. Cansino, R. Román-Collado, and L. Mundaca, “Car sharing services in sweden and spain: market, environmental and behavioural insights,” 2020, https://lucris.lub.lu.se/ws/portalfiles/portal/83575154/BE_USE_Project_Report_Phase_1_CSS_FINAL.pdf.

[72] A. Bento, J. Hughes, and D. Kaffine, “Carpooling and driver responses to fuel price changes: evidence from traffic flows in Los Angeles,” *Journal of Urban Economics*, vol. 77, no. 1, pp. 41–56, 2013.

[73] M. Ciasullo, O. Troisi, F. Loia, and G. Maione, “Carpooling: travelers’ perceptions from a big data analysis,” *The TQM Journal*, vol. 30, no. 5, pp. 554–571, 2018.

[74] J. Muhammad and N. Ali, “Analysis of commuters’ perceptions about carpooling service: a case study in Lahore,” *Journal of Research in Architecture and Planning*, vol. 28, no. 1, pp. 9–16, 2020.

[75] A. Dudziak, *Perception of Car Sharing Service in the Opinion of its Users*, Scientific Papers of Silesian University of Technology. Organization and Management Series, Silesian Voivodeship, Poland, 2020.

[76] É. M. S. Ramos, C. J. Bergstad, A. Chicco, and M. Diana, “Mobility styles and car sharing use in Europe: attitudes, behaviours, motives and sustainability,” *European Transport Research Review*, vol. 12, no. 1, p. 13, 2020.

[77] Y. Mehmood and V. Balakrishnan, “An enhanced lexicon-based approach for sentiment analysis: a case study on illegal immigration,” *Online Information Review*, vol. 44, no. 5, pp. 1097–1117, 2020.

[78] H. K. Janda, A. Pawar, S. Du, and V. Mago, “Syntactic, semantic and sentiment analysis: the joint effect on automated essay evaluation,” *IEEE Access*, vol. 7, pp. 108486–108503, 2019.

[79] H. Kaur, S. U. Ahsaan, B. Alankar, and V. Chang, “A proposed sentiment analysis deep learning algorithm for analyzing COVID-19 tweets,” *Information Systems Frontiers*, vol. 23, no. 6, pp. 1417–1429, 2021.

[80] Iso, “ISO/cd tr 14069 greenhouse gases— quantification and reporting of greenhouse gas emissions for organizations—guidance for the application of iso 14064-1,” 2020, https://www.iso.org/standard/78492.html.