

Integrating shared mobility into multimodal habits: A comparative analysis across shared micro- and 'macro'-mobility services

María Vega-Gonzalo ^{*} , Jose Cano-Leiva , Juan Gomez , José Manuel Vassallo

Centro de Investigación del Transporte (TRANSyT), Universidad Politécnica de Madrid, Spain

ARTICLE INFO

Keywords:

Shared mobility
Latent class analysis
Madrid
Multimodality
Urban mobility

ABSTRACT

Shared mobility services, which facilitate the access to different modes without the need to own them, is favouring increasingly multimodal mobility habits among urban travellers. Understanding how these new services are integrated into individuals' mobility patterns together with conventional modes is essential to understand the role that they play in improving accessibility and promoting sustainable urban mobility. To address this topic, two sub-samples have been extracted from a macro-survey conducted in the Region of Madrid: (i) users who have adopted shared micromobility (kick-scooter and bike-sharing) and (ii) users who have adopted *shared macromobility* (i.e., car- and moped-sharing). Using a Latent Class Analysis, we compare the profiles of each type of shared mobility user. The results show that three out of four classes can be found in both sub-samples. Specifically, a car-oriented class who rarely uses shared mobility, an active & public transport traveler class who mostly uses public transport and occasionally shared mobility; and a multimodal class who uses shared mobility around 3 and 4 times a week. In both cases, the most intensive users are clustered into classes whose mobility patterns and socio-economic profiles differ substantially. Finally, the model provides robust results regarding the impact of teleworking and place of residence on individuals' multimodal travel habits, factors for which the previous literature had provided limited conclusions. These results have been used to provide policy recommendations specific to the role that each type of service plays in individuals' mobility habits.

1. Introduction

The fast integration of ICT technologies in daily life has widened the supply of urban mobility options in the last few years, with the advent and expansion of new app-based mobility services, such as shared mobility, car-pooling or ride-hailing. This is taking place in a context of urgent need to decarbonise urban mobility and improve the liveability of urban areas. Aiming to move forward in this transition, local authorities are deploying different sustainable mobility policies to encourage a reduction of private car use in urban areas and induce a shift to more sustainable modes. Coercive ("push") measures, such as urban pricing, parking regulation or low-emission zones, have proven to be particularly effective in encouraging a modal shift towards greener modes (Kuss and Nicholas, 2022). However, it is essential to complement them with "pull" measures that provide feasible alternatives to the private car.

Shared mobility is regarded as a promising option to reduce car dependency and move urban mobility towards more sustainable

standards (Epprecht et al., 2014; Sopjani et al., 2020). This concept encompasses those services that can be rented on an on-demand, pay-per-use basis through a digital platform, without intermediaries, and currently includes a wide range of services and vehicles. It is possible to make a distinction between shared micromobility services, which commonly include e-kick scooters and bike-sharing, more suitable for conducting short trips; and those services, such as car-sharing and e-moped sharing, with greater potential to replace the private car and increase the utilization rates of current fleets (Narayanan and Antoniou, 2023). This variety makes it possible to satisfy the different purposes, needs and preferences of individuals, as they can choose the most convenient service for each situation. It should be noted that, in the context of this research, shared cars and mopeds will be jointly referred to under the term "*shared macromobility*", as opposed to shared micromobility. This grouping is based on common features, such as the requirement for a driver's licence and the possibility of reaching larger travel speeds compared to micromobility. This will be discussed in detail in Section 4, where the characteristics of the data are explained.

^{*} Corresponding author.

E-mail addresses: maria.vega.gonzalo@upm.es (M. Vega-Gonzalo), jose.cano.leiva@upm.es (J. Cano-Leiva), juan.gomez.sanchez@upm.es (J. Gomez), josemanuel.vassallo@upm.es (J.M. Vassallo).

<https://doi.org/10.1016/j.tranpol.2025.103840>

Received 26 March 2025; Received in revised form 3 September 2025; Accepted 30 September 2025

Available online 4 October 2025

0967-070X/© 2025 The Authors. Published by Elsevier Ltd. This is an open access article under the CC BY-NC license (<http://creativecommons.org/licenses/by-nc/4.0/>).

Shared mobility services are likely to have a significant impact on the mobility patterns of those who have adopted them. They can be incorporated into people's usual mobility choices by e.g. substituting the private car when traveling to areas of the city with access restrictions, or by complementing public transport in situations of poor transit accessibility. Reasonably, this impact will differ across the different types of shared services used and vehicle fleets available. To understand the role that shared mobility plays in the daily habits of individuals, it is necessary to explore how these services are currently combined with conventional urban modes (i.e., private car, public transport and active modes). It is also interesting to study which individual characteristics correlate with the different users' profiles. Such analysis will help target policy measures considering the trend towards integrating urban mobility modes through MaaS platforms with the aim of improving the efficiency and sustainability of urban mobility.

2. State of knowledge

Notwithstanding the relatively recent emergence of shared mobility, there is an extensive body of contributions in the scientific literature on these services (Castellanos et al., 2022), most of them focusing on identifying the key variables that determine their adoption and frequency of use. There is an overall agreement on the fact that the socio-economic characteristics as well as the travel profiles of shared mobility users is rather homogenous across the different available services (Blazanin et al., 2022; Mouratidis, 2022).

Shared mobility services are predominantly utilized by young to middle-aged men, as frequently observed in previous studies (e.g., Adnan et al., 2019 on bike-sharing; Laa and Leth, 2020 on kick-scooter sharing; Gilibert & Weymar, 2022 on moped-sharing; and Hjortset and Böcker, 2020 on car-sharing). Overall, individuals with higher income and education levels tend to adopt and use these services more frequently (see, for example, Blazanin et al., 2022 for e-scooter sharing; Reck and Axhausen, 2021 for bike-sharing; Vega-Gonzalo et al., 2024 for moped-scooter sharing; and Efthymiou and Antoniou, 2016 for car-sharing). The place of residence also seems to play an important role on travel habits concerning this kind of mobility. Individuals living closer to city centers (Aguilera-García et al., 2024; Nikiforiadis et al., 2021), enjoying a good availability public transport (Becker et al., 2017) and a more mixed land use pattern (Vega-Gonzalo et al., 2024) are more likely to have adopted shared mobility services.

Fewer studies have analysed the interactions of shared mobility with conventional modes of transport. Mouratidis (2022) for the case of Oslo, Norway found that car-sharing use is associated with a lack of access to a private car. The same was observed by Dias et al. (2024) for shared e-scooters in Braga, Portugal. Regarding the interaction and integration of shared mobility with public transport, some contributions have addressed this issue by either exploring spatio-temporal patterns of shared mobility trips in relation to the location of public transport stations (Kong et al., 2020; Radzimski and Dzięcielski, 2021), or conducting survey campaigns to measure people's intention to combine public transport and shared mobility services (Horjus et al., 2022; van Mil et al., 2021).

Noticeably, the scientific papers that exploit revealed or empirical data on the interaction between the use of shared mobility and conventional transport modes are scarce, and most of them have focused on bike-sharing services. For instance, Liu et al. (2020) evaluates the frequency of use of metro-bikeshare combination among users in Nanjing (China) by using GPS information data. They conclude that education level, individual income, travel time, and trip purpose are the key factors for a combined use. For the case of Seoul (South Korea), Kim (2023) analysed the modal integration of bike-sharing and public transport using integrated trip data of transit card holders. With a focus on spatio-temporal patterns, she found that the combined use is higher during weekdays. Other research pieces are based on reported data on mobility habits collected from survey campaigns. Zhang and Zhang

(2018) and Ma et al. (2022) explored the associations between bike-sharing and public transport use for 9 states in the US and Delft (The Netherlands) respectively, with diverging conclusions. Oostendorp & Haringhaus (2023) found no complementarity or substitution effect between public transport and scooter-sharing for Berlin, Germany, and Tarnovetckaia and Mostofi (2022) concluded a complementarity effect of carsharing for both public transport and private car use in the Moscow agglomeration (Russia). More recently, Narayanan and Antoniou (2023) evaluated the demand for ride-hailing, bike-sharing and carsharing simultaneously in the Region of Madrid by using data from the Household Mobility Survey, with less than 170 shared mobility trips.

As for the specific impact of shared mobility on car usage, previous literature has shown that the replacement of car trips is mostly achieved by either car-sharing (see e.g. Ceccato and Diana (2021) or Clewlow, 2016) or the combination of public transport and shared micromobility (Fan and Zheng, 2020; Saltykova et al., 2022). On the contrary, most contributions analysing the impact of shared micromobility services as stand-alone modes on car usage have found a limited replacement capacity of those services (see e.g. Teixeira et al., 2021 for bike-sharing or Weschke et al., 2022 for e-scooter sharing).

Other contributions have been conducted in the field of multimodality to identify the sociodemographic determinants of multimodal behaviours and attitudes (such as the willingness to adopt MaaS solutions). These studies found that age and income level are the most determinant factors of multimodal behaviour (see e.g. An et al., 2023; Deschaintres et al., 2021; Mehdizadeh and Ermagun, 2020). Private car users tend to be less multimodal, while the opposite is found for people using public transport (Alonso-González et al., 2020; Heinen, 2018; Molin et al., 2016). As for shared mobility services, Clewlow (2016) and Miramontes et al. (2017) observed that carsharing users consider a greater number of transport alternatives in their modal mix.

Recent contributions (see Nikiforiadis et al., 2023 or Kazemzadeh and Sprei, 2022) have pointed out the need for detailed analyses of mobility patterns that incorporate the use of shared mobility along with existing (conventional) transport modes in the modal mix. In this respect, three recent publications are worth noting. Gkavra et al. (2025) conduct a survey campaign and a Latent Class Analysis (LCA) to understand the key determinants of people's intention to use shared micromobility services in the future in three EU cities: Vienna, Brussels and Munich. Interestingly, they exploit respondents' frequency of use of different transport modes to identify the mobility and sociodemographic user profiles of bike and e-scooter sharing. Based on a subsample of more than 600 users, three main profiles were found: *Mobility chameleons*, *Car lovers*, and *Public transport fans*. Very similar research was developed by Fu et al. (2025) exploiting online survey data with more than 1,900 users and non-users of shared micromobility from the cities of Malmö, Greater Manchester and Utrecht, the latter with availability of e-mopeds. In an analogous way, Roig-Costa et al. (2024) conducted a survey to 900 shared mobility users in Barcelona (Spain) to understand their multimodal mobility patterns. They employed a K-modes algorithm to define clusters based on the respondent's declared weekly frequency of use of shared modes (bikesharing, kick scooter sharing and moped sharing). Notably, the use of conventional transport modes (public transport, private modes) is employed as class predictors, but not as part of the construction and identification of classes per se.

The conducted literature review reveals some research gap that this work aims to fill. First, this work includes frequency of use of car-sharing services, which has not been considered in previous contributions, despite the fact that it is probably the service with the greatest potential to substitute private cars. This is because it is likely the most accessible shared option for people who are used to traveling in their own cars, and the replacement potential of shared micromobility has been found to be limited, as discussed earlier in this section. Second, while most of the previous works have mainly focused on urban and suburban areas, this analysis is not limited to the main city (Madrid) but covers mobility patterns in neighbouring municipalities within the

metropolitan area, many of which also have a supply of shared modes available. Thus, the role of such new services in contexts of lower population density and accessibility to public transport is studied. Third, in previous works some common sampling problems (particularly, for studies on shared mobility) have been observed such underrepresentation of older people and oversampling of young people and students (see e.g. Gkavira et al., 2025; Fu et al., 2025; Roig-Costa et al., 2024; Aguilera-García et al., 2020). Our study addresses this issue by using a sample drawn from a comprehensive macro-survey that targets not only shared mobility users but also the general population. In fact, this work is based on the data gathered through a macro survey campaign addressed to more than 15,000 residents in the Region of Madrid (Spain) carefully designed to ensure gender, age, and spatial representativeness, providing a fairly accurate representation of current mobility habits.

The goal of this work is to understand how different types of shared mobility services (namely, shared micromobility and shared mobility) are integrated into individuals' mobility habits and the role they play in meeting the transport needs of various socio-economic segments. In this regard, the correlation between individual characteristics and place of residence within the metropolitan area, and the prevalence of different multimodal travel profiles will be analysed. To achieve this goal, two Latent Class Analyses (LCAs) have been conducted allowing to identify user profiles and assess the current role of these emerging services by examining how they are incorporated into people's mobility choices alongside conventional transport modes. The modelling results are interpreted to provide policy recommendations on how to harness the potential of different types of shared mobility services to fulfil mobility needs while ensuring sustainability.

The remaining of the paper is structured as follows. Section 2 presents the case study considered for this research, the Region of Madrid. Section 3 describes the macro-survey campaign carried out in this area together with a brief overview of the data collected. The methodological framework adopted in this research is described in Section 4, while Section 5 presents and comments on the main modelling results. Finally, Section 6 discusses the most important insights from the analysis, and Section 7 sets out the conclusions and proposes future research avenues.

3. Case study: the Region of Madrid

The Region of Madrid, with a total population of 6.7 million inhabitants, encompasses the third largest city and the third largest

metropolitan area in the EU. As in many other densely populated areas worldwide, the region can be divided into three main areas. First, the central districts of the city of Madrid, characterized by a very high population density and high levels of accessibility. Second, within the city of Madrid, the M-30 ring road separates the core city centre from the less central neighbourhoods of the city, for which the public transport supply, the shared mobility offer and accessibility level decline. Third, the metropolitan area, comprising neighbouring municipalities, which are closely linked to Madrid in economic, social and mobility terms. It should be noted that this metropolitan area encompasses rural municipalities with low population density and little economic activity.

The Region of Madrid follows the European pattern of a metropolitan area that concentrates a large part of its population and public transport supply in the core of the main city (see Fig. 1). Towards the peripheral areas, population density and transit accessibility—and, consequently, the modal share of sustainable modes—decrease. For instance, the modal share of the private car inside the M-30 ring road is around 20.3 %, while this percentage rises to 47.7 % for trips that start or end in the neighbouring municipalities in the metropolitan area. These trends have become more pronounced in recent decades due to a process of suburbanization accentuated after COVID19. The public transport network in the Region includes urban and interurban buses, metro, tram, and suburban train. Multimodality is present in public transport trips in the Region of Madrid. Specifically, 14.2 % of the trips in the city of Madrid are multimodal; while in the metropolitan area, this multimodality increases to 33.3 % (CRTM, 2019).

The city of Madrid imposes extensive restrictions on private car access. Firstly, there is a low-emissions zone comprising all districts within the first ring road (labelled as Madrid municipal area in Fig. 1), where access is restricted to the most polluting vehicles. Secondly, an even stricter zone covers the city's inner districts (Madrid city core in Fig. 1), where only low- and zero-emission vehicles are permitted (Tassinari, 2024). Thirdly, the city of Madrid has enacted parking regulations that severely limit parking times and impose high parking charges for the most polluting vehicles (González et al., 2022). In this regard, it is important to note that shared fleets in Madrid are fully electric, so they are exempt from access restrictions and curbside parking fees imposed by the local government.

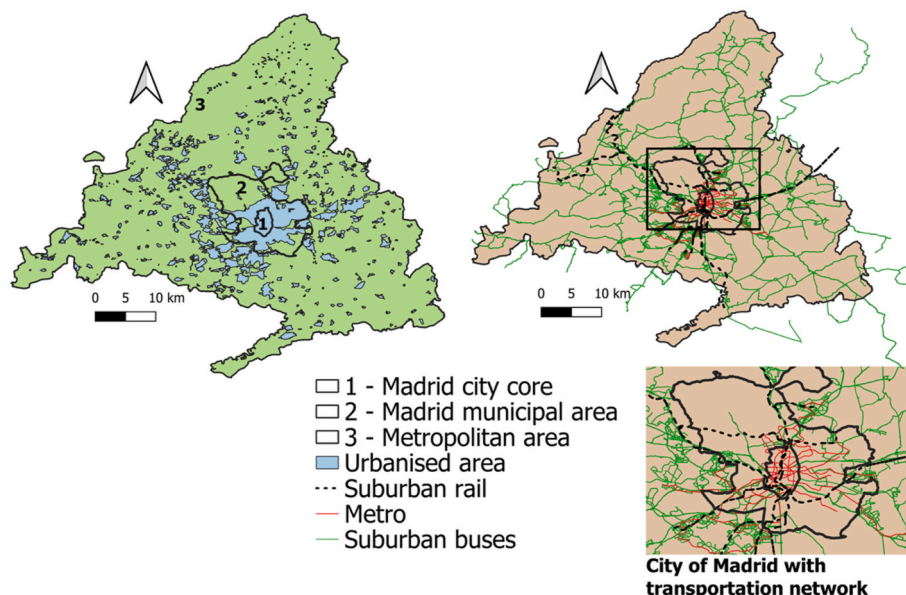


Fig. 1. Population density and public transport supply in the Region of Madrid.

3.1. Shared mobility ecosystem in the region of Madrid

Beyond the size and relevance of Madrid in the European context, its shared mobility system is one of the largest and most diverse in Europe, with practically all available services: bike-sharing, e-kick scooter sharing, e-moped sharing, and carsharing. With a fleet of almost 25,000 vehicles available, the Region offers more services than most of American and European metropolitan areas (Arias-Molinares and García-Palomares, 2020). Moreover, the city of Madrid has the largest number of shared mobility operators within the EU. These companies are mostly private and usually operate free-floating systems on a per-minute basis (between 0.25 and 0.45 Euro/minute). Interestingly, although most of the services are concentrated in the city of Madrid, there has been a recent expansion to some neighbouring municipalities of the metropolitan area. Fig. 2 shows the distribution of the different services across the Region and a detailed description of the available services is provided hereafter.

At the time of collecting the data for this research (late 2022), carsharing had 6 private operators, with a fleet of almost 4,000 cars distributed both in the city of Madrid and in some bordering municipalities such as Pozuelo, Majadahonda, or Alcobendas. There were 4 e-moped sharing operators with a fleet of around 7,500 scooters (Invers, 2022), mainly concentrated in the city of Madrid, but also present in some nearby municipalities additional to those of carsharing: Leganés, Getafe, Alcorcón, etc. As for e-kick scooter sharing, there were 3 operators providing a total fleet of almost 6,000 scooters. Finally, bike-sharing had 5 private operators offering free-floating services, and a public operator (Bicimad) that provides station-based services. As of late 2022, Bicimad had a fleet of 7,500 bicycles, offering both pay-per-minute and convenient flat fee schemes (Bicimad, 2024).

4. Data collection and exploratory analysis

The main data source for this study is a macro-survey conducted among residents in the Region of Madrid. This section details the design and content of the survey and presents an exploratory analysis of the data collected.

4.1. Survey design and content

The survey campaign was conducted between October and November 2022 by SIGMADOS, a global market research company with remarkable know-how in conducting mobility surveys. To ensure that the sample was representative of the residents in all the different areas of Region of Madrid, a stratified sampling process was carefully designed that took into account several variables such as gender, age and residential location. The latter is important, since some variables that could influence the frequency of use of conventional and shared modes and their role in mobility patterns (such as population density, car ownership rates and public transport accessibility) vary greatly depending on the geographic location of the residence.

The collection method combined Computer-Assisted Telephone Interviewing (CATI), which allowed reaching segments of the population with difficulties in accessing technologies; and Computer-Assisted Web Interviewing (CAWI), which allowed to reach those segments of the population whose lifestyles hinder phone localization. A total of 15,666 valid observations were obtained from the survey company, which was responsible for data cleaning, including the removal of incomplete responses and quality control procedures to ensure data validity. The questionnaire captured three inputs from respondents:

- *Individual's sociodemographic characteristics*: gender, age, level of education, occupation, monthly household income, dwelling type, household composition (no. children, adults and older people), and place of residence within the metropolitan area.
- *Travel-related variables*: number of cars in the household, access to private bike or e-scooter in the household, adoption of teleworking, and destination (municipality) of the most frequent trip on a weekday.
- *Declared frequency of use of conventional and shared transport modes*, namely: private car, public transport, private active modes (biking/walking), shared micromobility (bikesharing and e-kick scooter sharing) and shared macromobility (moped sharing and carsharing). It should be noted that the frequency of use of moped-sharing and carsharing, on the one hand, and shared bikes and kick-scooters, on the other hand, were jointly asked in the questionnaire. These responses are key for the subsequent analysis on user profiles and

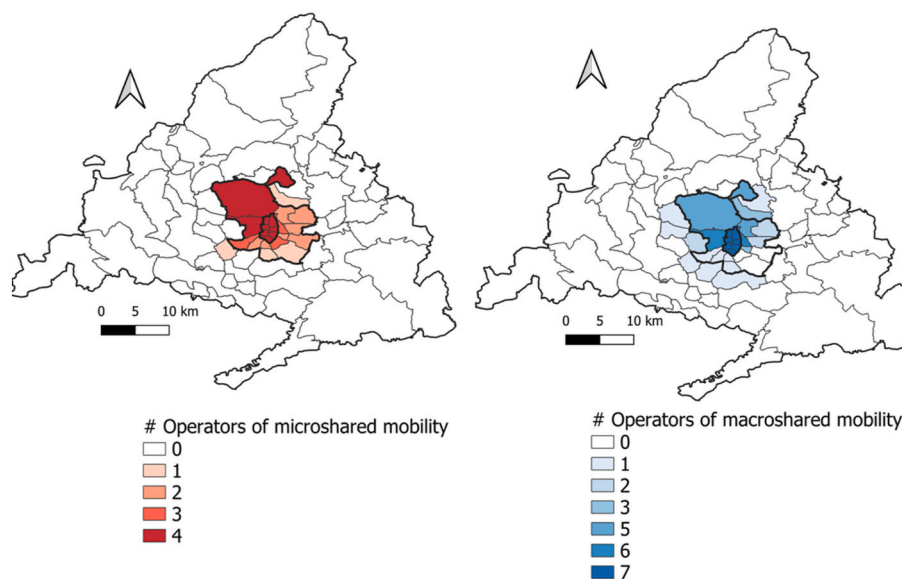


Fig. 2. Distribution of share micro- and macromobility operators in the Region of Madrid

Fig. 2a. Distribution of shared micromobility operators

Fig. 2b. Distribution of shared macromobility operators.

mobility habits (see Section 4.1 for more details on the categories considered in these variables).

The decision to merge these services in joint categories can be explained by both practical and analytical considerations. First, it allowed to reduce the number of questions in the survey to limit the answering burden. Second, it was intended to mitigate the imbalance between the proportion of users and non-users in the sample given the minority adoption of shared services. This allowed to improve the statistical robustness of the results. It has been considered that the merged services share several common features that are likely to influence their adoption and frequency of use in similar ways. For example, both mopeds and cars require the same driver's license in Spain, cannot use bike lanes, and the vehicles models operated in Madrid can achieve comparable speeds. Additionally, some previous works (see e.g. Aguilera-García et al., 2020) have found a positive and statistically significant correlation between the adoption of carsharing and moped-sharing. For those reasons, in the context of this work they have been grouped under the term *shared macromobility*. In contrast, bikes and kick-scooters, which fall under micromobility services, have been grouped into another category. This is because both shared bikes and kick scooters do not require a driver's license and can be ridden on bike lanes when available. These similarities are supported by previous literature that has observed similar features among users of these two services (see e.g. Reck and Axhausen, 2021).

For this study, two subsamples were considered based on individuals shared mobility usage patterns. The first subsample (*SMi subsample*) included individuals who have adopted shared micromobility (bike-sharing and/or e-kick scooter sharing), which a total of 969 observations (6.2 % of the total sample). Similarly, a second subsample (*SMA subsample*) included users of *shared macromobility* (moped sharing and/or carsharing), with a total of 1,654 observations (10.6 % of the total sample). Reasonably, these two subsets are not disjoint (666 individuals reported to use both means).

4.2. Data description

The descriptive statistics of the two subsamples mentioned above, and the non-sample users are found in Table 1. It also shows the results for the Wilcoxon-Mann Whitney tests to confirm the statistical significance of differences across the sub-samples. As a result of the stratified sampling process during the survey campaign, the distribution of the sample collected is representative of the Region of Madrid in terms of gender, age and residential location. The comparison with official statistics (INE, 2023) confirms that the level of education and employment are also representative.

4.2.1. Users vs. non-users of shared mobility

Reasonably, the majority of respondents in the total sample have not used shared mobility (86.3 %). The proportion of women and people over 55 years old among shared mobility users is noticeably lower than in the general population, in line with recent literature on shared mobility (see e.g., Madani et al., 2022 or Aguilera-García et al., 2021). Greater adoption of these services can be observed among people who live in Madrid city centre, are employed or have higher levels of education. Regarding travel-related variables, users of shared mobility show a higher probability of teleworking and lower car ownership levels, compared to non-users.

4.2.2. Users of shared micromobility vs. users of shared macromobility

The distribution across gender is similar between both types of shared mobility, despite a slightly higher proportion of men using shared micromobility, and the opposite in the case of *shared macromobility*. With respect to age, individuals over 55 years are more inclined to use *shared macromobility*, being this result consistent with the trend observed for retired individuals. In addition, users of *shared*

macromobility generally have a higher level of income. The data also reveals some differences on teleworking adoption between users of shared micromobility and *macromobility*. These differences are probably due to the fact that users of shared micromobility tend to be younger, as shown in our data and supported by prior literature (see e.g. Aguilera-García et al., 2022 or Reck and Axhausen, 2021). Since younger adults are more likely to adopt teleworking than older age groups (Peters et al., 2004; Tokey and Alam, 2023), they are expected to contribute to the differences observed.

Regarding travel-related variables, users of shared micromobility tend to live in more central areas, have higher levels of access to private active modes (bike/scooter), and are more likely to live in a car-free household (19 %, compared to 15.9 % for the *SMA* subsample). Some interesting differences can be found between both subsamples concerning mobility habits. Users of shared micromobility take public transport more frequently for their trips compared to *macromobility* users (62.1 % of respondents use it weekly, compared to 54.4 % for the *SMA* subsample). By contrast, the use of the private car is slightly higher for users of *shared macromobility* (63.0 % of respondents use it weekly) compared to the *SMi* subsample (60.6 %). Most shared mobility users have reported that they use these services with a frequency lower than weekly (61.7 % for the *SMi* subsample and 62.2 % for the *SMA* subsample, respectively), so they are mostly occasional users. These trends reinforce the results of Aguilera-García et al. (2020) and Vega-Gonzalo et al. (2024), who found that the frequency of use of shared mobility in Spanish urban areas is generally low.

5. Methodology – Latent Class Analysis

Latent Class Analysis (LCA) allows to study the relationships between a set of observed indicators to explore the underlying patterns that may exist in their distribution (Vermunt and Magidson, 2016). Based on these patterns, non-observable groups can be identified and observations (in this case, individuals) can be assigned to them. Unlike conventional cluster analysis, LCA does not deterministically assign each individual to a group but yields a probability of belonging to each of the identified classes. Membership in these classes is defined by the value of a categorical latent variable, and can subsequently be explained by a set of covariates (Hagenaars and McCutcheon, 2002) that characterize the individual, e.g., socio-economic attributes, etc. In this study, a LCA has been applied aiming to identify underlying profiles regarding the mobility habits of shared mobility users and explore how this new type of mobility services is combined with conventional urban modes to meet daily mobility needs. The models have been implemented in the software STATA 17, using the *gsem* function with *lclass* option, which allows to fit models with categorical latent variables.

5.1. Modelling of shared mobility user profiles

In this study, two LCA models have been estimated based on two different subsets of the total sample. First, the shared micromobility model (*SMi* Model) has been computed only for those who are users of shared micromobility services (i.e., shared-bike or/and shared e-kick-scooter). Second, the *shared macromobility* model (*SMA* Model) only considers users of carsharing or/and moped-scooter-sharing.

For both models, the LCA framework captures the heterogeneity between a set of four indicators that capture the individuals' self-reported frequency of use of: (i) conventional modes, differentiating between the private car/motorbike, public transport, and private active modes (biking and walking); and (ii) shared micromobility or *shared macromobility* services, depending on the model. The indicators capturing the use of conventional modes have five ordered categories (*Never*, *Occasionally*, *Between 1 and 2 times per week*, *Between 3 and 4 times per week*, *More than four times per week*). For the case of shared mobility, the indicators only have 3 categories (*Occasionally*, *Between 1 and 2 times per week*, *3 or more times per week*). This reduction is due to two main

Table 1

Distribution of socioeconomic attributes and travel-related variables in the complete dataset disaggregated between non-users, shared micromobility users and *shared macromobility* users.

		Non-users (86.3 %) n = 13,523	Shared micromobility users (6.2 %) n = 969	Wilcoxon-Mann Whitney test (sh-micro users vs. non-users)	Shared macromobility users (10.6 %) n = 1,654	Wilcoxon-Mann Whitney test (sh-macro users vs. non-users)
SOCIOECONOMIC ATTRIBUTES						
Gender	Male	45.0	51.2	$W = 7,490,207$, p -value	49.2	$W = 13,223,034$, p -value
	Female	55.0	48.8	< 0.005	50.8	< 0.005
Age	16–25 years old	10.1	13.8	$W = 8,683,910$, p -value	13.4	$W = 14,687,102$, p -value
	26–35 years old	20.1	25.4	< 0.005	24.6	< 0.005
	36–45 years old	18.5	30.8		23.8	
	46–55 years old	18.0	18.4		18.8	
	Over 55 years old	33.3	11.6		19.4	
Level of education	Primary education	4.1	0.9	$W = 6,509,492$, p -value	2.1	$W = 11,799,010$, p -value
	Lower-secondary education	7.9	6.3	< 0.005	5.9	< 0.005
	Vocational training	16.2	13.4		13.4	
	Baccalaureate	18.3	19.6		19.5	
Occupation	University education	53.5	59.8		59.1	
	Employed	70.3	78.1	$W = 7,697,581$, p -value	77.8	$W = 13,793,872$, p -value
	Student	5.7	10.3	< 0.005	7.8	< 0.005
	Homemaker, unemployed or retired	24.0	11.6		14.4	
Monthly household income ^a	Less than 1,000 €	7.3	6.5	$W = 8,229,614$, p -value =	6.5	$W = 4,870,244$, p -value =
	1,000 € - 1,500 €	17.2	16.4	0.05	15.8	0.207
	1,500 € - 2,000 €	18.5	22.4		18.5	
	2,000 € - 3,000 €	26.8	27.5		27.1	
	More than 3,000 €	30.2	27.2		32.1	
Teleworking	Yes	50.4	77.6	$W = 5,232,015$, p -value	70.8	$W = 10,170,842$, p -value
	No	49.6	22.4	< 0.005	29.2	< 0.005
Dwelling type	Single family dwelling	21.6	26.9	$W = 7,331,659$, p -value =	22.4	$W = 12,774,028$, p -value =
	Multiple family dwelling	70.6	62.7	0.020	68.5	0.675
	Other	7.8	10.4		9.1	
Place of residence	Madrid city core	20.9	38.9	$W = 8,616,262$, p -value	30.6	$W = 14,502,420$, p -value
	Madrid municipal area	27.4	26.5	< 0.005	30.3	< 0.005
	Metropolitan area	51.7	34.6		39.1	
TRAVEL-RELATED VARIABLES						
Number of cars per adult in the hh	No car	15.7	19.0	$W = 7,691,622$, p -value	15.9	$W = 13,279,634$, p -value
	0.01–0.5 cars/adult	43.7	48.7	< 0.005	48.4	< 0.005
	0.51–0.75 cars/adult	8.3	5.7		7.7	
	>0.75 cars/adult	32.3	26.6		28.0	
Access to private modes	Access to e-kick- scooter	5.06	21.8	$W = 5,883,200$, p -value	12.4	$W = 11,790,508$, p -value
	Access to bike	24.0	45.9	< 0.005	31.7	< 0.005
Destination of the most frequent trip	Urban area of residence	48.8	48.3	$W = 5,528,224$, p -value	49.3	$W = 11,795,584$, p -value
	Urban area other than area of residence	47.7	45.1	< 0.005	45.9	< 0.005
	I prefer not to answer	3.5	6.6	$W = 6,902,387$, p -value =		$W = 12,665,304$, p -value =
Frequency of use of public transport	Never	27.9	6.3	0.148		0.768
	Occasionally	27.2	31.6	$W = 5,744,344$, p -value	13.3	$W = 11,213,442$, p -value
	1-2 times/week	12.0	20.9	< 0.005	31.8	< 0.005
	3-4 times/week	8.8	20.1		18.3	
	More than 4 times per week	24.1	21.1		14.4	
Frequency of use of private car	Never	22.7	15.8		22.2	
	Occasionally	15.9	23.6	$W = 7,533,653$, p -value	17.3	$W = 12,846,662$, p -value =
	1-2 times/week	16.2	26.1	< 0.005	19.7	0.448
	3-4 times/week	10.9	13.6		21.8	
	More than 4 times per week	34.3	20.9		13.6	
Frequency of use of active modes	Never	44.1	8.3	$W = 5,361,976$, p -value	22.9	$W = 10,975,259$, p -value
	Occasionally	15.0	32.3	< 0.005	26.1	< 0.005
	1-2 times/week	8.0	22.4		16.6	
	3-4 times/week	8.7	16.2		12.7	
	More than 4 times per week	24.2	20.8		21.7	
Frequency of use of shared kick- scooter/bike	Never	100 %	n/a	n/a	30.6	n/a
	Occasionally	n/a	61.7		37.4	
	1-2 times/week	n/a	21.6		18.7	

(continued on next page)

Table 1 (continued)

		Non-users (86.3 %) n = 13,523	Shared micromobility users (6.2 %) n = 969	Wilcoxon-Mann Whitney test (sh-micro users vs. non-users)	Shared macromobility users (10.6 %) n = 1,654	Wilcoxon-Mann Whitney test (sh-macro users vs. non-users)
Frequency of use of shared car/moped- scooter	More than 3 times per week	n/a	16.7		13.3	
	Never	100 %	63.7	n/a	n/a	n/a
	Occasionally	n/a	21.4		62.2	
	1-2 times/week	n/a	8.9		19.2	
	More than 3 times per week	n/a	6.0		18.6	

^a The percentages of these variables do not sum up to 100 % because there was a “I prefer not to answer” category.

facts: (1) since the study purely focuses on current users of this kind of services, the category *Never* does not apply in this case; and (2) the last two categories have been merged due to their low presence in the data.

The class predictors or covariates that have been tested are the same for both models, and include: i) the *socio-economic attributes* of the individual (gender, age, education, occupation, household monthly income and dwelling type, and place of residence within the Region of Madrid); and ii) *travel-related variables* (number of cars per adult owned by the household, teleworking regime, and frequent destination on weekdays). The variable that shows whether individuals have access to a private bike or kick-scooter has only been included in the shared micromobility model. The structure of the models has been graphically represented in Fig. 3.

It should be noted that, before constructing the models, the optimal number of classes that constitute the latent categorical variables must be determined. Most previous analyses have approached this decision comparing the goodness-of-fit and the parsimony of several models with different number of classes using the Akaike Information Criterion (AIC) or the Bayesian Information Criterion (BIC), see e.g., Molin et al. (2016) or Rafiq and McNally, (2021). Our analysis follows the same criteria and compares the indexes for models with number of classes between 2 and 8.

5.2. Mathematical specification of the models

This sub-section describes formally the model estimated in this research. This description as well as the notation is based on the theoretical description of LCA in Vermunt and Magidson (2016).

The indicators (observed responses on mode frequency of use) takes

value y_{it} , where i identifies each individual and t the indicators, so that in our case $t = \{\text{private car/motorbike (car), public transport (pt), private active modes (am), shared micromobility/macromobility (sm)}\}$. The indicators, which have an ordinal nature, take values $1 \leq m \leq M$, with M being the number of alternatives, which is 5 for $y_{i,car}, y_{i,pt}, y_{i,am}$, and 3 for $y_{i,sm}$. On the other hand, x is the latent variable that captures the heterogeneity between indicators, that can take values $1 \leq k \leq K$, with K being the number of classes identified in the observed data. Finally, the set of p covariates that are considered to determine the membership of an individual i to the assigned class are contained in the vector $\mathbf{z}_i^{cov}$.

LCA assumes local independence, that is, given the value of the latent variable, the indicators are conditionally independent. If this assumption is met, it can be considered that correlations between the observed indicators are captured by a latent categorical variable that segments the individuals in the sample in homogeneous classes. Under this assumption, the probability of obtaining a specific response pattern $y_{i,car} = m_{car}, y_{i,pt} = m_{pt}, y_{i,am} = m_{am}, y_{i,sm} = m_{sm}$ can be formulated as:

$$P(y_{i,car} = m_{car}, y_{i,pt} = m_{pt}, y_{i,am} = m_{am}, y_{i,sm} = m_{sm}) = \sum_{x=1}^4 P(x | \mathbf{z}_i^{cov}) \prod_{t=1}^5 P(y_{it} = m_t | x, \mathbf{z}_i^{cov}) \quad (1)$$

This is the product of the probability that an individual belongs to class x given the covariates that capture her/his characteristics, and the probability of a specific response pattern for the indicators given that the individual belongs to class x and has a set of covariates $\mathbf{z}_i^{cov}$.

First, the probability of an individual belonging to class x has been modelled as a multinomial latent variable using the specification shown in Equation (2):

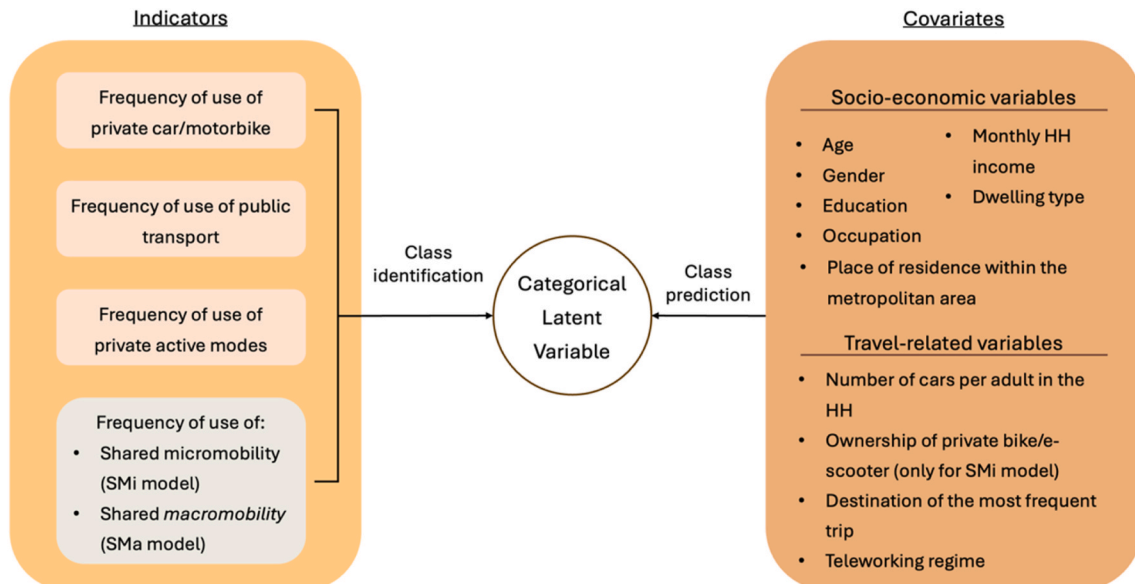


Fig. 3. Structure of the LCA models.

$$P(x|z_i^{cov}) = \frac{\exp\left(\gamma_{x0} + \sum_{r=1}^R \gamma_{xr} \cdot z_{ir}^{cov}\right)}{\sum_{x'=1}^K \left(\exp \gamma_{x'0} + \sum_{r=1}^R \gamma_{x'r} \cdot z_{ir}^{cov}\right)} \quad (2)$$

where γ_{x0} is the intercept, γ_{xr} the regression coefficient for each covariate r , and x' the reference category of the categorical latent variable. The intercept γ_{x0} represent the log-odds of an individual belonging to class x when all independent variables are set to zero, which occurs when the individual characteristics correspond to the reference categories established for all the covariates z_i^{cov} . Second, the response or indicator variables follow an ordinal distribution, so they can be modelled using an adjacent-category logit. The mathematical formulation of a certain individual's probability of having declared a frequency of use m_t for mode t , given the class to which she/he belongs and her/his characteristics, can be found in Equation (3). This specification has been obtained by posing the restriction $\beta_{mp} = \beta_p \cdot y_m^*$ to the regression coefficient of a multinomial logit, with y_m^* being the score of the m category of the frequency of use, β_{m0} the intercept of the ordinal logistic regression, and β_p the regression coefficients of the covariates.

$$P(y_{it} = m_t | x) = \frac{\exp(\eta_{m|x, z_i}^t)}{\sum_{m'=1}^M \exp(\eta_{m'|x, z_i}^t)} \eta_{m|x, z_i}^t = \log \left(\frac{P(y = m | z_i^{cov})}{\left[\prod_{m'=1}^M P(y = m' | z_i^{cov}) \right]^{1/M}} \right) \\ = \beta_{m0} + \sum_{p=1}^P \beta_p \cdot y_m^* \cdot z_{ip}^{cov} \quad (3)$$

6. Results

This section presents the results of class identification and class prediction for the SMi and SMa models. Based on the goodness-of-fit measures of models with classes ranging from 3 to 8, the optimal number of classes for both the SMi and SMa models was found to be 4. Different indicators, such as the BIC, the Entropy R^2 and the change in

log-likelihood were considered to support this decision. The fit indexes for all the considered models can be found in [Appendix 1](#).

The classes were labelled based on the most frequent travel patterns observed considering both conventional and shared transport modes. Following the “class identification” phase, which analyses user profiles based on their declared weekly combination of modes, the study examined correlations between class membership and individual characteristics. This second phase, corresponding to the “class prediction” stage of the LCA, utilized the distribution of individual attributes across classes and applied the multinomial logit model to identify the covariates determining the membership to a specific class (see [Fig. 3](#)).

6.1. Shared micromobility (SMi) model

The travel patterns of the four classes identified by the SMi model have been graphically represented in [Fig. 4](#). The distribution of individual characteristics across classes can be found in [Table 2](#). In this table, two different types of results have been summarised. First, the percentages represent the distribution of each covariate on each of the latent classes. This information aims to show the socio-economic profile of each latent class, regardless of whether the variable has an statistically significant class-conditional membership probability. Second, to provide information on which of these variables are statistically significant to explain an individual's belonging to a certain class, the p-values of the class-conditional membership probabilities have been symbolically included using asterisks. The complete modelling results for the class prediction are in [Appendix B \(Table B.1\)](#).

1 Car oriented + rare use of shared micromobility.

The first class includes those who predominantly rely on the private car to cover their daily mobility needs. The members of this class have a probability of 0.71 of using the private car more than once a week, while this probability drops to 0.33 for using public transport more than once a week. As for shared micromobility or private active modes (biking/walking), this class uses them rarely. In fact, almost the whole subsample (97 %) uses shared micromobility only

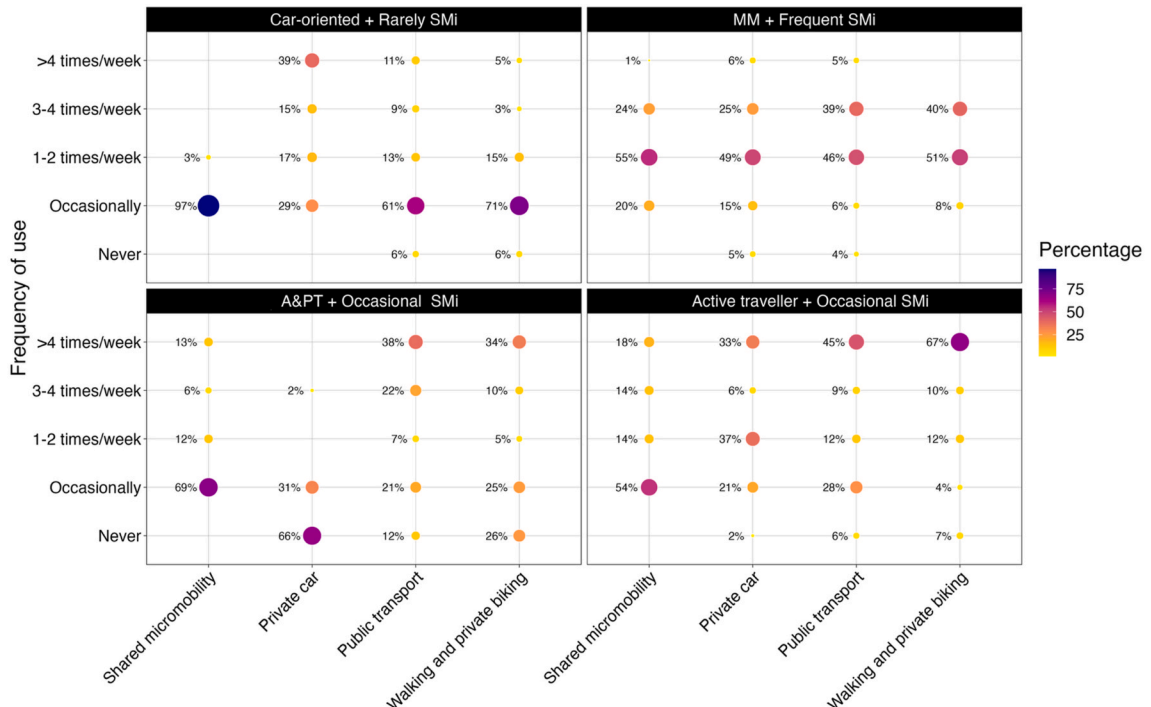


Fig. 4. Modelling results for the class identification part of the shared micromobility model.

Table 2

Sociodemographic and travel-related variables for each class of shared micromobility sub-sample.

		Class 1 Car-oriented + Rarely SMI	Class 2 MM + Frequent SMI	Class 3 A&PT + Occasional SMI	Class 4 Active traveler + Occasional SMI
% OF SUB-SAMPLE		32.3 %	27.3 %	21.1 %	19.3 %
SOCIOECONOMIC ATTRIBUTES					
Gender (<i>Reference: Male</i>)	Male	52.3 %	48.3 %	51.0 %	55.6 %
	Female	47.7 %	51.7 %	49.0 %	44.4 %
Age (<i>Reference: 16 – 25 years old</i>)	16–25 years old	7.3 %	14.9 %	23.3 % (**)	6.4 %
	26–35 years old	23.0 %	26.0 %	22.8 % (*)	25.1 %
	36–45 years old	30.0 %	35.7 %	24.3 %	28.7 %
	46–55 years old	24.8 %	17.1 % (*)	12.9 %	23.4 %
	Over 55 years old	15.0 %	6.3 % (*)	16.8 %	16.4 %
Level of education (<i>Reference: Primary education</i>)	Primary education	0.9 %	0.4 %	1 %	1.2 %
	Lower-secondary education	6.7 %	7.8 %	8.9 %	0.6 %
	Vocational training	11.9 %	17.8 %	17.8 %	6.4 %
	Baccalaureate	21.4 %	19.7 %	17.8 %	17.5 %
Occupation (<i>Reference: Employed</i>)	University education	59.0 %	54.3 %	54.5 %	74.3 %
	Employed	84.4 %	69.5 %	66.8 %	91.2 %
	Student	6.1 %	19.0 % (***)	14.4 % (*)	0.6 %
	Homemaker, unemployed or retired	9.5 %	11.5 %	18.8 % (*)	8.2 %
Monthly household income ^a (<i>Reference: Less than 1,000 €</i>)	Less than 1,000 €	4.0 %	4.8 %	8.9 %	5.3 %
	1,000 € - 1,500 €	14.4 %	10.8 %	19.3 %	11.1 %
	1,500 € - 2,000 €	17.1 %	32.0 % (***)	15.8 %	7.6 %
	2,000 € - 3,000 €	24.8 %	27.1 %	17.3 %	21.6 %
	More than 3,000 €	23.9 %	17.8 %	12.9 %	40.9 % (*)
Place of residence (<i>Reference: Madrid city core</i>)	Madrid city core	20.5 %	47.2 %	44.6 %	54.4 %
	Madrid municipal area	32.7 %	19.3 % (***)	26.7 % (**)	25.7 % (***)
	Metropolitan area	46.8 %	33.5 % (***)	28.7 % (**)	19.9 % (***)
TRAVEL-RELATED VARIABLES					
Number of cars per adult in the hh (<i>Reference: No car</i>)	No car	3.4 %	8.2 %	74.3 %	3.5 %
	0.01–0.5 cars/adult	14.1 %	13.4 %	9.9 % (***)	15.8 %
	0.51–0.75 cars/adult	39.8 %	55.4 %	8.4 % (***)	49.7 %
	>0.75 cars/adult	42.8 %	23.0 % (**)	7.4 % (***)	31.0 %
Teleworking (<i>Reference: No</i>)	Yes	72.8 %	93.3 % (***)	70.3 %	71.3 %
Access to private modes (<i>Reference: No</i>)	Access to e-kick-scooter (Yes)	14.1 %	42.0 % (***)	14.9 %	14.0 %
	Access to bike (Yes)	48.3 %	44.2 %	37.6 %	53.8 %
Destination of the most frequent trip (<i>Reference: Urban area of residence</i>)	Urban area of residence	41.0 %	36.4 %	65.4 %	59.1 %
	Urban area other than area of residence	52.9 %	55.0 %	24.7 %	38.0 %
	I prefer not to answer	6.1 %	8.6 %	9.9 %	2.9 %

*** p-value <0.005, ** p-value <0.05, * p-value <0.100. For each variable, the reference category is always the first one.

^a The percentages of these variables do not sum up to 100 % because there was a “I prefer not to answer” category.

occasionally. Given that the characteristics of car-oriented individuals are well established by previous literature (Soza-Parra and Cats, 2023) and this class encompasses the biggest proportion of individuals within the SMI subsample, it has been chosen as reference category for the class prediction multinomial model. For this reason, the characterization of this class can only be studied through the sample distributions displayed in Table 2.

The socio-demographic characteristics and mobility habits of this class are consistent with what would be anticipated based on existing literature. Its members are predominantly male adults over 35 years old, with high levels of education. In terms of income, this class seems to be rather accommodated with almost half of the class living in households with a monthly income above 2,000€. As expected, this class has the highest levels of car ownership and a greater probability of residing in nearby municipalities of the metropolitan area (46.8 %), that is, outside Madrid city.

2 Multimodal + frequent use of shared micromobility.

The second class identified by the model includes individuals with high levels of overall mobility that use both conventional modes and shared micromobility between 1 and 4 times per day. However, these users show a slightly higher tendency to use public transport and active modes more frequently, suggesting that shared micromobility and the private car are used as complementarity alternatives for specific purposes once or twice per week. The identification of this

class is aligned with previous findings on shared mobility (see e.g. Gkavra et al., 2025 or Fu et al., 2025).

The class prediction model yields interesting results regarding the socio-economic characteristics of this class. In terms of age, its members seem to be mainly younger adults below 45 years old. With respect to the reference class, the model shows that being a student increases the probability of belonging to this class, although it should be noted that almost 70 % of the members of this class are currently working. This class includes the highest share of teleworkers, which might suggest a relationship between this working arrangement and an increased level of multimodality. Both the sample distributions and the class prediction model (see Table 2 and B.1) indicate that this class is predominantly composed by middle-income individuals, who mainly reside in the city of Madrid (especially in the city centre, where the availability of public transport and shared micromobility is noticeably higher). All this is coherent with a more frequent use of active modes and public transport together with a lower use of costlier modes such as the private car or shared micromobility.

3 Active & public transport travellers (A&PT) + occasional use of shared micromobility.

The active & public transport travellers class includes individuals who rely mainly on public transport, private active modes (walking and biking) and to a lesser extent on an occasional use of shared micromobility. It can be observed that 60 % of them uses public

transport more than three times/week, and around 44 % uses private active modes with this frequency. As for shared micromobility, 70 % uses it occasionally, but it should be noted that a reasonable percentage (13 %) makes a very intensive use of these services (more than 4 times per week).

The modelling results for the class prediction (see [Appendix B](#)) suggest that, while age groups are fairly distributed in this class, and the majority of them are employed, young individuals under 25 years old and students are more likely to belong to this class. Its members have restricted access to private vehicles. In fact, this class has the greatest proportion of individuals who reside in car-free households (74.3 %). As in the previous classes, the place of residence seems to significantly determine this profile. They are mainly living in the city of Madrid and tend to be middle-low-income individuals. Altogether, the characteristics of this class hint towards an important role of shared mobility among those who, as a result of limited access to the private car, rely mainly on active modes and public transport.

4 Active travellers + occasional use of shared micromobility.

The fourth class has been labelled as active travellers since its most remarkable feature is a very high probability of using private active modes more than 4 times/week (0.67). As for their use of shared micromobility, 54 % of them uses it occasionally, but it is worth noting that this class has the highest probability of using shared micromobility services more than three times a week (0.32). Additionally, when looking at their use of public transport and private cars, these users are revealed as rather multimodal, albeit with considerable heterogeneity. For the case of public transport, most members of this class (45 %) use it more than 4 times/week, although there is also a relevant share (34 %) that uses it occasionally or never. Finally, an intensive use of the private car seems to be less frequent in this class, with 60 % of the people using it less than three times per week. A class quite like this one was also found by [Fu et al. \(2025\)](#) for their analysis in Utrecht, where these users combined a frequent use of private bikes with an occasional use of shared micromobility, but with a slightly higher preference for shared bikes.

The class prediction model (see [Table 2](#) and [B.1](#)) provides limited statistically significant results for this class, likely because it includes

a quite small size (19.3 % of the SMi subsample). Noticeably, they are the class with the highest proportion of residents in Madrid city core, which is consistent with their high use of active modes and public transport. In terms of socio-economic characteristics, income emerges as a key determinant, with high-income individuals (monthly income above 3,000 Euro) being the most likely to belong to this class, even if the car-oriented class is taken as a reference. This effect contrasts with the results recently obtained in three cities in Central Europe (Brussels, Munich, and Vienna) by [Gkavra et al. \(2025\)](#), who found high-income groups to be the most inclined ones to display car dependent profile. On the other hand, it is aligned with previous works on shared mobility in the city of Madrid, which observed that the use of these services can significantly reduce car dependency among high-income groups ([Vega-Gonzalo et al., 2024](#)). Beyond the modelling results, the distributions of covariates (see [Table 2](#)) shows that this class includes the highest percentage of males, workers and university-educated individuals, and the lowest proportion of students. Finally, this class presents relatively high levels of car ownership, with most people (81.0 %) living in households with more than 0.5 cars per adult. This characterization suggests that this class could encompass traditionally car-dependent profiles who have growingly adopted shared micromobility as a result of its wide availability in Madrid city centre. However, as mentioned above, many of the effects reported here are not statistically significant.

6.2. Shared macromobility (SMA) model

The SMA model reveals the existence of four latent classes, whose travel patterns have been graphically represented in [Fig. 5](#). The distribution of individual characteristics across classes can be found in [Table 3](#), which has been structured following the same methodology as [Table 2](#). This table includes both the percentages representing the distribution of each covariate on each of the latent classes and the corresponding p-values of the class-conditional membership probabilities, symbolically included using asterisks. The complete modelling results for the class prediction are in [Appendix B \(Table B.2\)](#).

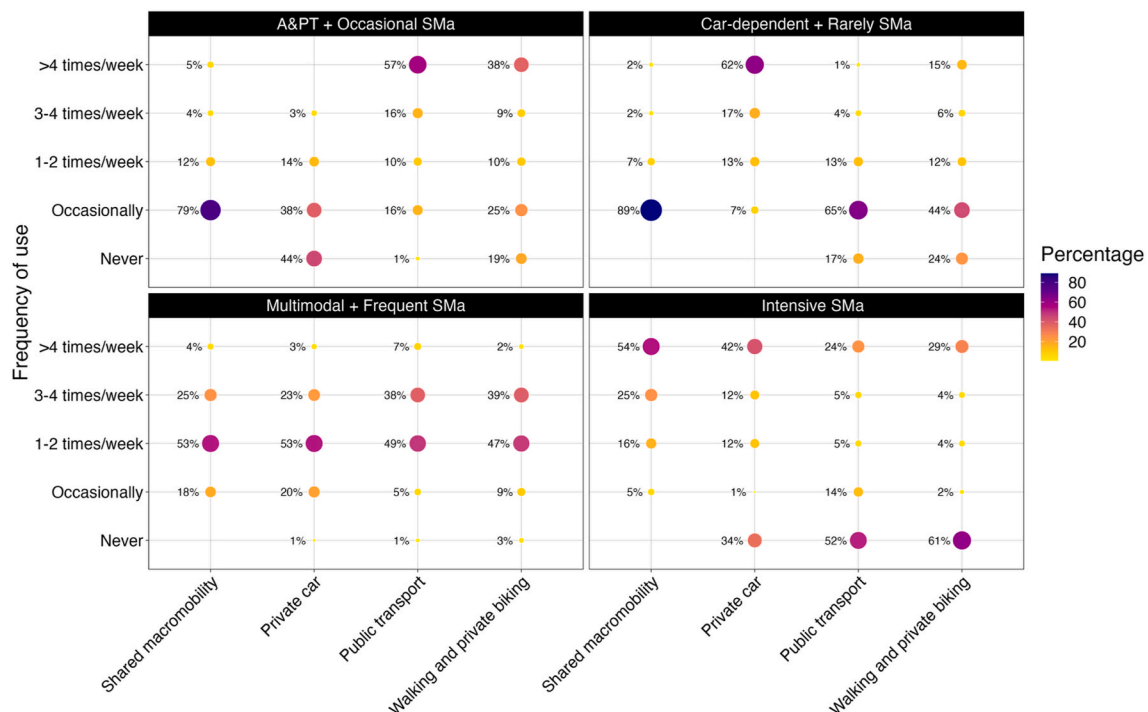


Fig. 5. Modelling results for the class identification part of the *shared macromobility* model.

Table 3Sociodemographic and travel-related variables for each class of the *shared macromobility* model.

		Class 1 Car-dependent + Rarely SMa	Class 2 A&PT + Occasional SMa	Class 3 MM + Frequent SMa	Class 4 Intensive SMa
% OF SAMPLE		37.8 %	31.2 %	18.8 %	12.2 %
SOCIOECONOMIC ATTRIBUTES					
Gender (Reference: Male)	Male	61.1 %	41.6 %	44.6 %	34.9 %
	Female	39.0 %	58.4 % (***)	55.4 % (**)	65.1 % (***)
Age (Reference: 16 – 25 years old)	16–25 years old	6.0 %	15.3 %	14.9 %	12.0 %
	26–35 years old	24.6 %	21.9 % (**)	23.7 %	19.8 % (***)
	36–45 years old	28.5 %	19.2 % (***)	32.9 %	15.1 % (***)
	46–55 years old	25.3 %	16.6 % (***)	18.7 %	16.7 % (**)
	Over 55 years old	15.6 %	27.1 %	9.8 %	36.5 %
Level of education (Reference: Primary education)	Primary education	1.0 %	1.7 %	0.6 %	7.8 %
	Lower-secondary education	3.8 %	4.8 %	7.6 %	11.5 %
	Vocational training	10.5 %	13.5 %	14.9 %	19.3 %
	Baccalaureate	21.5 %	16.4 %	22.5 %	21.4 % (**)
	University education	63.3 %	63.4 %	54.4 %	40.1 % (**)
Occupation (Reference: Employed)	Employed	91.7 %	68.9 %	72.2 %	69.3 %
	Student	2.1 %	9.9 % (***)	17.4 % (***)	5.7 %
	Homemaker, unemployed or retired	6.2 %	21.3 % (***)	10.4 % (***)	25.0 % (*)
Monthly household income ^a (Reference: Less than 1,000 €)	Less than 1,000 €	3.3 %	8.9 %	4.1 %	8.9 %
	1,000 € - 1,500 €	10.7 %	14.5 %	13.9 %	16.2 %
	1,500 € - 2,000 €	9.4 %	13.5 %	30.7 % (***)	17.7 %
	2,000 € - 3,000 €	24.3 %	19.9 %	28.5 %	19.3 % (*)
	More than 3,000 €	38.2 %	22.6 % (**)	16.5 % (***)	17.2 % (*)
Place of residence (Reference: Madrid city core)	Madrid city core	23.7 %	36.6 %	41.8 %	16.7 %
	Madrid municipal area	35.1 %	33.9 % (*)	25.3 % (***)	17.2 %
	Metropolitan area	41.2 %	29.6 % (*)	32.9 % (***)	66.2 % (***)
TRAVEL-RELATED VARIABLES					
Number of cars per adult in the hh (Reference: No car)	0 cars	1.9 %	40.4 %	7.0 %	15.1 %
	0.01–0.5 cars/adult	8.6 %	19.7 %	12.7 %	14.6 %
	0.51–0.75 cars/adult	39.8 %	28.4 % (***)	60.4 %	35.4 % (***)
	>0.75 cars/adult	49.8 %	11.4 % (***)	19.9 % (**)	34.9 % (***)
Teleworking (Reference: No)	Yes	73.3 %	64.6 %	95.9 % (***)	40.1 % (***)
Destination of the most frequent trip* (Reference: No)	Urban area of residence	44.7 %	64.6 %	41.8 %	38.0 %
	Urban area other than area of residence	50.9 %	33.5 % (***)	50.6 %	55.2 % (*)

*** p-value <0.005, ** p-value <0.05, * p-value <0.100. For each variable, the reference category is always the first one.

^a The percentages of these variables do not sum up to 100 % because there was a “I prefer not to answer” category.

1 Car dependent + occasional use of *shared macromobility*.

This class encompasses individuals for whom private cars play a pivotal role in their mobility routines. In fact, 79 % of the members of this class use the car three or more times a week and show a very low frequency of use for all other modes of transport. Notably, more than 80 % of respondents stated that they never or only occasionally utilize public transportation, and almost 90 % reported occasional use of *shared macromobility*. When it comes to active modes, this pattern is slightly moderated, with a probability of 0.66 of never or occasionally using them. This class has been selected as the reference for the class prediction model, for the same reasons outlined for the SMi analysis.

The socio-economic profile of this class corresponds to the typical characteristics of car-dependent groups (see Table 3). Its members seem to be predominantly male, with the class prediction model showing that females are less likely to belong to this class than to any of the other ones. The members of this class show high levels of education and employment (92 %), and consequently, it is the class with the highest percentage of members in the highest-income category (38.2 %). Reasonably, car ownership levels in this class are the highest across the four classes. With respect to commuting habits, approximately half of the members are employed outside of their place of residence, while a majority proportion (73 %) engage in some form of teleworking arrangement.

2 Active & public transport travellers (A&PT) + occasional use of *shared macromobility*.

This class has been labelled as active & public transport travellers since it displays sustainable travel habits. Its members are characterized by a very frequent use of public transport, with a probability of 0.73 of using it three or more times a week. Private active modes are used less frequently but still play an important role in the mobility patterns of this class, with 38 % of members using this option more than 4 times a week. It is noteworthy that 44 % of this class never use the car and 38 % use it only occasionally. Finally, *shared macromobility* is predominantly used occasionally (80 %).

In terms of socio-demographics, it can be seen (Table 3) that this class includes a fair representation of all the age categories, but noticeably most of its members are either young adults under 35 or older adults aged over 55. This effect is corroborated by the class prediction model (see Table 3 and Table B.2), which shows that middle-aged adults are significantly less likely to belong to this class. Concerning occupation, the sample distributions shows that this class is mainly composed by employed people, but students, homemakers and unemployed or retired individuals are more likely to belong to this class, which is confirmed by the class prediction. All this is coherent with a lower presence of high-income people in this class compared to the car-oriented class. Finally, the level of car ownership, the place of residence and the commuting habits of this class are fully consistent with their declared travel behaviour, as they mainly live within the municipality of Madrid (70.4 %), own few cars (40.4 % of the members are car-free) and mostly work within the same urban area of residence. The class prediction model confirms the statistical significance of these results.

3 Multimodal + frequent use of *shared macromobility*.

This class shows high levels of overall mobility, with most of its members declaring to use all available modes, including *shared macromobility*, with a rather high frequency (between 1 and 4 times/week). A more nuanced analysis of their travel patterns reveals that public transport and private active modes play a more important role in their travel habits. While more than 40 % of individuals declared using each of them between 3 and 4 times/week, these percentages go down to 29 % and 26 % for *shared macromobility* and the private car, respectively.

The socio-economic profile of this class seems to be that of a middle-class individual who lives in Madrid city centre but works in a different municipality and enjoys teleworking arrangements. These features are aligned with the declared travel habits, since people seem to prioritize public transport and active modes (which are widely available and feasible alternatives in the city centre) but opt for the private car and shared micromobility with relatively high frequency, probably for commuting purposes. The need to complement the car with *shared macromobility* could be explained by the fact that the members of this class are probably not having permanent access to a private car, since 60 % of the individuals in this class lives in households owning between 0.5 and 0.75 cars per adult. It is also noteworthy that the multimodal class displays the highest percentage of students across the four classes (17.4 %), a result confirmed by statistically significant coefficients for this category in the class prediction model (see Table B.2). This indicates that, although students are not majority in this class, this type of individuals is more likely to belong to this class than to the reference.

4 Intensive *shared macromobility*.

The travel patterns of the smallest class (12 % of the users) seem to be mainly characterized by an intensive use of *shared macromobility*, with 54 % of the class using it more than 4 times a week and another 25 % between 3 and 4 times a week. With respect to conventional modes, there seems to be an inclination towards a frequent use of the private car. Nevertheless, considerable heterogeneity of travel patterns is observed in this class, since 34 % of these individuals never used the car, and a non-negligible percentage uses public transport (24 %) and active modes (29 %) very intensively.

Reasonably, this heterogeneity of travel habits also leads to some diverging trends in terms of the socio-demographic profile. There is a high percentage of women (65.1 %) and adults over 55 years old (36.5 %). This age distribution would seem initially surprising, but it is fully in line with previous contributions analysing the usage of shared-mopeds in Spain (see Vega-Gonzalo et al., 2024). Education and income levels are lower than in other classes, which is confirmed by the class prediction model and coherent with the significantly lower adoption of teleworking compared to the rest of the classes. It is particularly interesting that two thirds of the people of this class reside outside Madrid city, in nearby municipalities in the metropolitan area, where the supply of shared mobility is limited. As the supply of shared micromobility outside of Madrid, these results would hint towards these users using the private car to reach the city of Madrid and then relying on *shared macromobility* to move within the city. In fact, a closer analysis of the data shows that 63 % of the members of this class that live in the metropolitan area, use both the private car and *shared macromobility* intensively. This idea may be reinforced by the high levels of car ownership of this class, which are only surpassed by the car-dependent class, as reflected in the class prediction model. Additionally, it is noteworthy that almost 30 % of this class uses public transport more than three times a week. This distribution in addition to the reasonably extensive supply of inter-urban and suburban trains connecting Madrid with its surrounding municipalities, suggests that a minority of users may combine private cars, public transport, and *shared macromobility* to fulfil their mobility needs.

6.3. Comparison of SMi and SMa models

The comparison of the SMi and SMa models reveals similarities and some interesting differences between the latent profiles in the shared micro and *macromobility* samples.

In both cases, the LCA identifies a class which uses the car as main mode and groups the largest share of users (32 % of shared micromobility users and 38 % for *shared macromobility* users). Despite both classes being identified by their reliance on the car, their comparison shows that an intensive use of the car is clearly less likely in the SMi class, whose members seem to also rely on public transport. By contrast, car-dependent users of *shared macromobility* use the car daily and complement it more likely with active private modes and *shared macromobility*. Regarding socio-economic features, both classes are quite similar, except for the fact that car-dependent users of *shared macromobility* are wealthier. It is particularly interesting to note that in both cases more than two thirds of this class live outside Madrid city.

The *active & public transport* profile is also found in both models, although its presence is greater among *shared macromobility* users (32 %) than among shared micromobility users (21 %). The latter are more likely to use public transport intensively, with 57 % using it more than 4 times a week, than the former, for which the percentage goes down to 38 %. Consistently, the probability of never using the private car is higher among shared micromobility users (0.66) compared to shared *macromobility* users (0.44). The use of shared mobility within the *active & public transport* class varies between the two models. While 31 % of shared micromobility users rely on these services at least once a week, only 21 % of *shared macromobility* users use them with the same frequency. Taking the frequency of use of all the considered modes together the results suggest that *active & public transport* travellers using shared micromobility exhibit lower overall mobility levels on shared modes than their *macromobility* counterparts. These findings align with the socio-economic characteristics of each class: in the shared micromobility sample, 70 % of *active & public transport* travellers are car-free and belong to the lowest income group, whereas in the *shared macromobility* sample, the proportion of car-free users decreases to 40 %, and income levels are moderate. Apart from this, the sociodemographic profile in both cases is quite similar.

The class of multimodal travellers, who frequently utilize shared mobility, is also identified in both models. In fact, the distributions of frequency of use for all the considered modes, as well as the socio-economic profiles, are practically identical for both classes. The analysis of the data reveals that almost 80 % of the micromobility users in this class, also belong to the multimodal class in the *shared macromobility* model, indicating that these travellers are also largely multimodal in terms of both types of shared modes. However, it is important to note that the sizes of this profile vary considerably between the two sub-samples, representing 27.3 % of shared micromobility and 18.9 % of *shared macromobility* users.

Finally, the models reveal two remaining non-comparable classes. The SMi model includes an *active mode traveler* category, characterized by occasional use of shared micromobility, whereas the SMa model identifies a class defined by intensive *shared macromobility* use. Notably, these are the smallest classes in both models, but they are the ones that use shared services the most. These findings indicate that intensive users of shared mobility are a clear minority in both micro and macro (see Table 1) and exhibit distinct profiles depending on the type of service. While intensive *shared macromobility* users are largely concentrated in a single category, with a 0.79 probability of using *shared macromobility* more than three times per week, intensive shared micromobility users appear more dispersed across different classes.

7. Discussion and policy lessons

The analysis of each model, as well as their comparison, allows to draw some key insights that can support the development of sustainable

mobility policies accounting for the role of shared mobility.

As could be expected, shared micromobility seems to be used mainly to complement an intensive use of public transport and active modes, while *shared macromobility* is mostly complementing the private car. The active & public transport traveler class is considerably larger for the *shared macromobility* sample, but this is probably due to the fact that, for shared micromobility users, the more sustainable behaviours fall into two classes: the active & public transport travellers and the active modes travellers, which sum up to almost 40 % of the sample. In conclusion, it can be observed that shared micromobility users tend to display more sustainable travel patterns than users of *shared macromobility*. However, this insight should be taken with caution, as *shared macromobility* could be an essential element in the mobility patterns of those whose place of residence limits their ability to choose sustainable options. In terms of policy development, these results indicate that the different types of shared mobility play very different roles in people's multimodal habits and should therefore be regulated according to different frameworks and considerations. On the one hand, the regulation of shared micromobility should aim to strengthen its role as a complement to public transport and to ensure that young and low-income population groups with limited access to private cars have sufficient availability of shared vehicles and can afford to use this type of service when needed. To this end, subsidy schemes that facilitate the access to these modes for specific purposes and among disadvantaged social groups should be explored (Delbosch & Thigpen, 2024; Ma et al., 2020). On the other hand, the potential of shared macromobility would probably be better exploited if it became more available in the outskirts of metropolitan areas, as the results show that the most intensive users are those living in low-density areas and using it as a complement to the private car or residents in the city centre who have their working place in a different municipality and are highly multimodal.

The place of residence emerges as a key factor in explaining user profiles. The SMi model clearly shows that car-dependent users are the most likely to live outside the city of Madrid, probably due to their lower population density urban setting and lower availability of public transport. Additionally, the analysis of the sample distributions shows more nuanced results. It seems reasonable that most people belonging to the active travellers' class (54.4 %) live in Madrid city centre, due to their high walking accessibility. It is also interesting to note that, taking the SMi and SMa models, 33 % of the multimodal class (who uses shared services frequently) live outside Madrid city. This suggests that shared mobility can also be incorporated in their mobility patterns despite not being widely available in their places of residence. In the same line, the SMa model shows that users living in the metropolitan area (that is, outside Madrid city) have higher probability of belonging to the class of intensive users of *shared macromobility*, even if the car-dependent class is taken as a reference. These insights are particularly relevant in the scientific literature as only Fu et al. (2025) have considered the place of residence as an explanatory factor of multimodal behaviour including shared mobility, with limited results. Moreover, the fact that the most frequent users of shared mobility tend to live outside Madrid, despite these services being available only within the city, suggests that shared mobility is a practical option for navigating areas with Low Emission Zones and parking regulations, as it is the case in the city of Madrid.

As for the socio-economic characteristics relevant in explaining multimodal profiles that incorporate the use of shared mobility, income and occupation can be highlighted. In both SMi and SMa models, middle-income individuals tend to belong to the multimodal classes, but for the rest of the classes the effect of income seems to differ considerably between users of shared micro- and *macromobility*. In the SMi sample, active travellers are the wealthiest ones. On the contrary, active & public transport travellers include the highest percentage of low-income people, which reinforces the need to ensure that the use of shared micromobility by these users, either to access public transport or when existing services are insufficient, does not become an excessive economic burden for this socio-economic segment. In the SMa model,

wealth seems to be concentrated in the car-dependent class, which is consistent with individuals who can afford high levels of car ownership and the usage of *shared macromobility*.

Finally, the effect of teleworking in both models indicates that teleworkers seem to be especially flexible travellers that are significantly more likely to adopt multimodal habits that also include shared mobility services. It should be noted that this relation is difficult to compare to previous works given the limited evidence obtained in this regard. The only contribution worth mentioning is Ellidér (2020), who found no difference between teleworkers and non-teleworkers when considering the combination of conventional modes for commuting. This difference between previous findings and ours suggest that the increase in teleworking adoption rates in recent years and the introduction of shared modes in individuals' mobility habits have influenced the relationships between teleworking and multimodal patterns.

8. Conclusions and further research

This research has led to several contributions that go beyond the results obtained by previous investigations concerning the role of shared mobility services on individuals' multimodal patterns. On the one hand, the calibration of two separate models for shared micromobility and *shared macromobility* helped us identify the traveler profiles that exist for each type of shared mobility and understand, through comparison, the different roles they play in shaping multimodal habits. On the other hand, the variety of community typologies (urban, sub-urban and rural) that are represented in the sample, together with the thorough design and stratification methods of the survey, have allowed us to draw some relevant conclusions regarding two essential drivers of transport behavior: the place of residence and the adoption of teleworking regimes. It is worth noting that their influence has been barely addressed in previous works analyzing multimodality behaviors that incorporate shared mobility.

These models have shown that three classes are in general terms rather similar for the different types of shared mobility services. A car-oriented or car-dependent class who combines an intensive use of the car with shared mobility; an active & public transport traveler who mainly combines it with public transport and active modes and a multimodal traveler who uses all conventional and shared modes frequently. In both models a fourth class displaying the most intensive usage of shared mobility has been identified. This class shows diverging mobility patterns for users of each type of service. Taking the results altogether they suggest that while shared bikes and e-scooters are mostly related to public transport users, shared mopeds and cars tend to complement the private car. In that respect, it can be concluded that shared micromobility users display a more sustainable travel behavior, which is probably explained to some extent to being more likely to live closer to the center of Madrid where accessibility to environmentally friendly modes is higher.

Notwithstanding the contributions of this work, some limitations can be mentioned that open the way for future research avenues. First, the survey design aggregated shared bikes with kick-scooters, and shared cars with mopeds, when capturing individuals' frequency of use. While the analysis has value, it does represent a limitation, as some of these services (e.g. shared mopeds and shared cars) are not entirely equivalent in terms of functionality, safety, and user characteristics, or usage behaviour. Future research would therefore benefit from collecting more disaggregated data on the use of different types of shared vehicles to better capture service-specific behaviours. Second, the model shows that the scarcity of intensive users of shared mobility hinders a clearer identification of both their multimodal travel profile and their socio-economic characteristics. In that respect, a more in-depth analysis focusing on intensive users could provide further insights into the role of shared modes in the mobility patterns of those who use them almost daily. Third, as this study analyses multimodality as a combination of modes in individuals' mobility habits, it would be relevant to

understand which modes are used for specific activities and purposes to better understand the drivers behind the combined use of shared and conventional modes. Finally, the consideration of latent variables capturing subjective preferences and attitudes regarding environmental awareness, car pride or technological savviness, would improve the results obtained in our analysis.

CRediT authorship contribution statement

María Vega-Gonzalo: Writing – original draft, Software, Methodology, Formal analysis, Data curation, Conceptualization. **Jose Cano-**

Leiva: Writing – original draft, Formal analysis. **Juan Gomez:** Writing – review & editing, Supervision, Investigation, Funding acquisition, Conceptualization. **José Manuel Vassallo:** Writing – review & editing, Funding acquisition.

Acknowledgments

This research was carried out within the framework of project TED2021-129239B-I00 (GREENSHARE) funded by MICIU/AEI/10.13039/501100011033 and European Union NextGenerationEU/PRTR.

APPENDIX A

Table A.1

Number of classes selection for the LCA for shared micromobility

No. of classes	Obs.	LL	LL change	df	AIC	BIC	Entropy
3	969	−5110,96		44	10309,92	10524,48	0,7950
4	969	−5016,15	94,81	59	10150,29	10437,99	0,8042
5	969	−4976,8	39,35	74	10101,61	10462,45	0,7055
6	969	−4942,17	34,63	86	10056,33	10475,69	0,6947
7	969	−4931,84	10,33	94	10051,68	10510,05	0,6846
8	969	−4920,43	11,41	102	10044,85	10542,23	0,6741

LL = final log-likelihood of the model; LL change = final log-likelihood change respect to the previous model; df = degrees of freedom; AIC = Akaike's information criterion; BIC = Bayesian information criterion; Entropy = Entropy R^2 .

Table A.2

Number of classes selection for the LCA for *shared macromobility*

No. of classes	Obs.	LL	LLchange	df	AIC	BIC	Entropy
3	1,654	−9976,48		44	20040,96	20283,92	0,6216
4	1,654	−9863,99	112,49	59	19845,98	20171,77	0,6535
5	1,654	−9844,99	19	72	19833,98	20231,55	0,6268
6	1,654	−9799,91	45,08	89	19777,81	20269,26	0,6461
7	1,654	−9799,87	0,04	96	19791,74	20321,83	0,5964
8	1,654	−9787,24	12,63	109	19792,48	20394,3	0,5926

LL = final log-likelihood of the model; LL change = final log-likelihood change respect to the previous model; df = degrees of freedom; AIC = Akaike's information criterion; BIC = Bayesian information criterion; Entropy = Entropy R^2 .

APPENDIX B

Table B.1

Results of class prediction in the SMi model

SOCIOECONOMIC ATTRIBUTES		Latent class (ref: Car-oriented + Rarely SMi)		
		Multimodal + Frequent SMi	A&PT + Occasional SMi	Active traveler + Occasional SMi
		Coeff (std. error)	Coeff (std. error)	Coeff (std. error)
Age (ref: 16 – 25 years old)	26–35 years old	–	−1.201** (0.510)	–
	36–45 years old	–	−0.772* (0.440)	–
	46–55 years old	−0.446* (0.232)	–	–
	Over 55 years old	−0.446* (0.232)	–	–
Occupation (ref: Employed)	Student	1.400*** (0.371)	0.831* (0.430)	–
	Homemaker, unemployed or retired	–	0.831* (0.430)	–
Monthly household income (ref: Less than 1,000 €)	1,000 € - 1,500 €	–	–	–
	1,500 € - 2,000 €	0.901*** (0.250)	–	–
	2,000 € - 3,000 €	–	–	–
	More than 3,000 €	–	–	0.574* (0.302)
Place of residence (ref: City core)	Madrid municipal area	−1.046*** (0.305)	−0.742** (0.366)	−1.031*** (0.346)
	Metropolitan area	−1.114*** (0.292)	−0.742** (0.366)	−1.588*** (0.468)
TRAVEL-RELATED VARIABLES				
Number of cars per adult in the hh (ref: No cars)	0.01–0.5 cars/adult	–	−3.300*** (0.502)	–
	0.51–0.75 cars/adult	–	−4.100*** (0.480)	–

(continued on next page)

Table B.1 (continued)

SOCIOECONOMIC ATTRIBUTES		Latent class (ref: Car-oriented + Rarely SMi)		
		Multimodal + Frequent SMi	A&PT + Occasional SMi	Active traveler + Occasional SMi
		Coeff (std. error)	Coeff (std. error)	Coeff (std. error)
Teleworking (ref: No)	>0.75 cars/adult	−0.679** (0.254)	−4.335*** (0.530)	–
Access to private modes (Reference: No)	Yes	1.450*** (0.348)	–	–
	Access to e-kick-scooter (Yes)	1.011*** (0.232)	–	–
	Access to bike (Yes)	–	–	–
Constant		−1.359*** (0.435)	3.477*** (0.621)	0.116 (0.318)

*** p-value <0.005, ** p-value <0.05, * p-value <0.100.

Table B.2

Results of class prediction in the SMA model

SOCIOECONOMIC ATTRIBUTES		Latent class (ref: Car-dependent + Rarely SMA)		
		A&PT + Occasional SMA	MM + Frequent SMA	Intensive SMA
		Coeff (std. error)	Coeff (std. error)	Coeff (std. error)
Gender (ref: Male)	Female	0.719*** (0.170)	0.438** (0.194)	0.838*** (0.215)
Age (ref: 16 – 25 years old)	26–35 years old	−0.433** (0.217)	–	−0.763*** (0.246)
	36–45 years old	−0.544*** (0.195)	–	−0.763*** (0.246)
	46–55 years old	−0.544*** (0.195)	–	−0.763** (0.294)
	Over 55 years old	–	–	–
Level of education (ref: Primary education)	Lower-secondary education	–	–	–
	Vocational training	–	–	–
	Baccalaureate	–	–	−0.540** (0.270)
	University education	–	–	−0.602** (0.238)
Occupation (ref: Employed)	Student	1.372*** (0.348)	2.419*** (0.374)	–
	Homemaker, unemployed or retired	1.142*** (0.303)	1.256*** (0.345)	0.612* (0.332)
Monthly household income (ref: Less than 1,000 €)	1,000 € - 1,500 €	–	–	–
	1,500 € - 2,000 €	–	1.184*** (0.223)	–
	2,000 € - 3,000 €	–	–	−0.402* (0.212)
	More than 3,000 €	−0.395** (0.185)	−0.873*** (0.240)	−0.373* (0.212)
Place of residence (ref: City core)	Municipal area	−0.303* (0.178)	−0.712*** (0.232)	–
	Metropolitan area	−0.303* (0.178)	−0.932*** (0.234)	0.905*** (0.240)
TRAVEL-RELATED VARIABLES				
Number of cars per adult in the hh (ref: 0 cars)	0.01–0.5 cars/adult	–	–	–
	0.51–0.75 cars/adult	−1.846*** (0.182)	–	−1.058*** (0.268)
	>0.75 cars/adult	−2.863*** (0.224)	−1.321** (0.219)	−1.313*** (0.276)
Teleworking (ref: No)	Yes	–	2.447*** (0.375)	−0.732*** (0.208)
Destination of the most frequent trip (ref: Urban area of residence)	Urban area other than area of residence	−0.721*** (0.166)	–	−0.421* (0.232)
Constant		1.819*** (0.266)	−2.702*** (0.431)	0.671* (0.0.377)

*** p-value <0.005, ** p-value <0.05, * p-value <0.100.

Data availability

The authors do not have permission to share data.

References

- Adnan, M., Altaf, S., Bellemans, T., et al., 2019. Last-mile travel and bicycle sharing system in small/medium sized cities: user's preferences investigation using hybrid choice model. *J. Ambient Intell. Hum. Comput.* 10, 4721–4731. <https://doi.org/10.1007/s12652-018-0849-5>.
- Aguilera-García, Á., Gomez, J., Sobrino, N., 2020. Exploring the adoption of moped scooter-sharing systems in Spanish urban areas. *Cities* 96, 102424. <https://doi.org/10.1016/j.cities.2019.102424>.
- Aguilera-García, Á., Gomez, J., Antoniou, C., Vassallo, J.M., 2022. Behavioral factors impacting adoption and frequency of use of carsharing: a tale of two European cities. *Transp. Policy* 123, 55–72. <https://doi.org/10.1016/j.TRANPOL.2022.04.007>.
- Alonso-González, M.J., Hoogendoorn-Lanser, S., van Oort, N., Cats, O., Hoogendoorn, S., 2020. Drivers and barriers in adopting Mobility as a Service (MaaS)—A latent class cluster analysis of attitudes. *Transport. Res. Pol. Pract.* 132, 378–401. <https://doi.org/10.1016/j.tra.2019.11.022>.
- An, Z., Heinen, E., Watling, D., 2023. The level and determinants of multimodal travel behavior: does trip purpose make a difference? *International journal of sustainable transportation* 17 (2), 103–117. <https://doi.org/10.1080/15568318.2021.1985195>.
- Arias-Molinares, D., García-Palomares, J.C., 2020. Shared mobility development as key for prompting mobility as a service (MaaS) in urban areas: the case of Madrid. *Case Studies on Transport Policy* 8 (3), 846–859. <https://doi.org/10.1016/j.CSTP.2020.05.017>.
- Becker, H., Loder, A., Schmid, B., Axhausen, K.W., 2017. Modeling car-sharing membership as a mobility tool: a multivariate probit approach with latent variables. *Travel Behaviour and Society* 8, 26–36. <https://doi.org/10.1016/j.TBS.2017.04.006>.
- Bicimad, 2024. Bicimad en 8 tips. <https://www.bicimad.com/bicimad>, 06.07.24.
- Blazanin, G., Mondal, A., Asmussen, K.E., Bhat, C.R., 2022. E-scooter sharing and bikesharing systems: an individual-level analysis of factors affecting first-use and use

- frequency. *Transport. Res. C Emerg. Technol.* 135, 103515. <https://doi.org/10.1016/J.TRC.2021.103515>.
- Castellanos, S., Grant-Muller, S., Wright, K., 2022. Technology, transport, and the sharing economy: towards a working taxonomy for shared mobility. *Transp. Res.* 42 (3), 318–336. <https://doi.org/10.1080/01441647.2021.1968976>.
- Ceccato, R., Diana, M., 2021. Substitution and complementarity patterns between traditional transport means and car sharing: a person and trip level analysis. *Transportation* 48 (4), 1523–1540. <https://doi.org/10.1007/S11116-018-9901-8/TABLES/5>.
- Clewlow, R.R., 2016. Carsharing and sustainable travel behavior: results from the San Francisco Bay area. *Transp. Policy* 51, 158–164. <https://doi.org/10.1016/J.TRANPOL.2016.01.013>.
- CRTM, Consorcio Regional de Transportes de Madrid, 2019. Encuesta domiciliaria de movilidad en día laborable de 2018 en la Comunidad de Madrid. edM2018. Noviembre de 2019. Retrieved from. <https://www.crtm.es/conocenos/planificacio-n-estudios-y-proyectos/encuesta-domiciliaria/edm2018.aspxon06.07.24>.
- Delbos, A., Thigpen, C., 2024. Who uses subsidized micromobility, and why? Understanding low-income riders in three countries. *Journal of Cycling and Micromobility Research* 2, 100016.
- Deschaintres, E., Morency, C., Trépanier, M., 2021. Measuring changes in multimodal travel behavior resulting from transport supply improvement. *Transp. Res. Rec.* 2675 (9), 533–546. <https://doi.org/10.1177/03611981211003104>.
- Efthymiou, D., Antoniou, C., 2016. Modeling the propensity to join car-sharing using hybrid choice models and mixed survey data. *Transp. Policy* 51, 143–149. <https://doi.org/10.1016/J.TRANPOL.2016.07.001>.
- Eldér, E., 2020. Telework and daily travel: new evidence from Sweden. *J. Transport Geogr.* 86, 102777. <https://doi.org/10.1016/j.jtrangeo.2020.102777>.
- Epprecht, N., von Wirth, T., Stünzi, C., Blumer, Y.B., 2014. Anticipating transitions beyond the current mobility regimes: how acceptability matters. *Futures* 60, 30–40. <https://doi.org/10.1016/J.FUTURES.2014.04.001>.
- Fan, Y., Zheng, S., 2020. Dockless bike sharing alleviates road congestion by complementing subway travel: evidence from Beijing. *Cities* 107, 102895. <https://doi.org/10.1016/J.CITIES.2020.102895>.
- Fu, X., van Lierop, D., Ettema, D., 2025. Shared micromobility in multimodal travel: evidence from three European cities. *Cities* 158, 105664. <https://doi.org/10.1016/j.cities.2024.105664>.
- Gilbert, M., Weymar, A., 2022. Case study on the use and adaptation of SEAT MÓ motorbike sharing service in Barcelona in COVID-19 pandemic year. *Case Studies on Transport Policy* 10 (1), 591–597. <https://doi.org/10.1016/J.CSTP.2022.01.019>.
- Gkavra, R., Susilo, Y.O., Grigolon, A., Geurs, K., Roeder, O., 2025. Mobility chameleons: the current and potential users of shared micromobility. *Travel Behaviour and Society* 39, 100967. <https://doi.org/10.1016/j.tbs.2024.100967>.
- Gonzalez, J.N., Gomez, J., Vassallo, J.M., 2022. Do urban parking restrictions and low emission zones encourage a greener mobility? *Transport. Res. Transport Environ.* 107, 103319. <https://doi.org/10.1016/J.TRD.2022.103319>.
- Hagenaars, J.A., McCutcheon, A.L. (Eds.), 2002. *Applied Latent Class Analysis*. Cambridge University Press.
- Heinen, E., 2018. Are multimodals more likely to change their travel behaviour? A cross-sectional analysis to explore the theoretical link between multimodality and the intention to change mode choice. *Transport. Res. F Traffic Psychol. Behav.* 56, 200–214. <https://doi.org/10.1016/j.trf.2018.04.010>.
- Hjortset, M.A., Böcker, L., 2020. Car sharing in Norwegian urban areas: examining interest, intention and the decision to enrol. *Transport. Res. Transport Environ.* 84, 102322. <https://doi.org/10.1016/J.TRD.2020.102322>.
- Horjus, J.S., Gkiotsalitis, K., Nijenstein, S., Geurs, K.T., 2022. Integration of shared transport at a public transport stop: mode choice intentions of different user segments at a mobility hub. *Journal of Urban Mobility* 2, 100026. <https://doi.org/10.1016/j.urbmob.2022.100026>.
- INE, 2023. Población de 16 y más años por nivel de formación alzado, sexo y comunidad autónoma. [Data set]. Porcentaje respecto del total de cada comunidad. Retrieved from <https://www.ine.es/jaxiT3/Tabla.htm?t=6347&L=0>. (Accessed 20 February 2025).
- INVERS, 2022. *Global Moped Sharing Market Report Q3 2022*.
- Kazemzadeh, K., Sprei, F., 2022. Towards an electric scooter level of service: a review and framework. *Travel behaviour and society* 29, 149–164. <https://doi.org/10.1016/j.tbs.2022.06.005>.
- Kim, K., 2023. Investigation of modal integration of bike-sharing and public transit in Seoul for the holders of 365-day passes. *J. Transport Geogr.* 106, 103518. <https://doi.org/10.1016/j.jtrangeo.2022.103518>.
- Kong, H., Jin, S.T., Sui, D.Z., 2020. Deciphering the relationship between bikesharing and public transit: modal substitution, integration, and complementation. *Transport. Res. Transport Environ.* 85, 102392. <https://doi.org/10.1016/j.trd.2020.102392>.
- Kuss, P., Nicholas, K.A., 2022. A dozen effective interventions to reduce car use in European cities: lessons learned from a meta-analysis and transition management. *Case studies on transport policy* 10 (3), 1494–1513. <https://doi.org/10.1016/j.cstp.2022.02.001>.
- Laa, B., Leth, U., 2020. Survey of E-scooter users in Vienna: who they are and how they ride. *J. Transport Geogr.* 89, 102874. <https://doi.org/10.1016/J.JTRANGEO.2020.102874>.
- Liu, Y., Ji, Y., Feng, T., Timmermans, H., 2020. Understanding the determinants of young commuters' metro-bikeshare usage frequency using big data. *Travel behaviour and society* 21, 121–130. <https://doi.org/10.1016/j.tbs.2020.06.007>.
- Ma, X., Yuan, Y., Van Oort, N., Hoogendoorn, S., 2020. Bike-sharing systems' impact on modal shift: a case study in delft, the Netherlands. *J. Clean. Prod.* 259, 120846. <https://doi.org/10.1016/j.cstp.2022.11.002>.
- Madani, N., Creemers, L., Moeinaddini, M., Saadi, I., Cools, M., 2022. Low-cost shared mobility alternatives in rural areas: a case study of ride-sharing benches in the german-speaking community of Belgium. *Case Stud. Transp. Pol.* 10 (4), 2393–2400.
- Mehdizadeh, M., Ermagun, A., 2020. "I'll never stop driving my child to school": on multimodal and monomodal car users. *Transportation* 47 (3), 1071–1102. <https://doi.org/10.1007/s11116-018-9949-5>.
- Miramontes, M., Pfortner, M., Rayaprolu, H.S., Schreiner, M., Wulforst, G., 2017. Impacts of a multimodal mobility service on travel behavior and preferences: user insights from Munich's first mobility station. *Transportation* 44, 1325–1342. <https://doi.org/10.1007/s11116-017-9806-y>.
- Molin, E., Mokhtarian, P., Kroesen, M., 2016. Multimodal travel groups and attitudes: a latent class cluster analysis of Dutch travelers. *Transport. Res. Pol. Pract.* 83, 14–29. <https://doi.org/10.1016/j.tra.2015.11.001>.
- Mouratidis, K., 2022. Bike-sharing, car-sharing, e-scooters, and uber: who are the shared mobility users and where do they live? *Sustain. Cities Soc.* 86, 104161. <https://doi.org/10.1016/J.SCS.2022.104161>.
- Narayanan, S., Antoniou, C., 2023. Shared mobility services towards Mobility as a Service (MaaS): what, who and when? *Transport. Res. Pol. Pract.* 168, 103581.
- Nikiforiadis, A., Paschalidis, E., Stamatiadis, N., Paloka, N., Tsekoura, E., Basbas, S., 2023. E-scooters and other mode trip chaining: preferences and attitudes of university students. *Transport. Res. Pol. Pract.* 170, 103636. <https://doi.org/10.1016/j.tra.2023.103636>.
- Peters, P., Tijdens, K.G., Wetzels, C., 2004. Employees' opportunities, preferences, and practices in telecommuting adoption. *Inf. Manag.* 41 (4), 469–482. [https://doi.org/10.1016/S0378-7206\(03\)00085-5](https://doi.org/10.1016/S0378-7206(03)00085-5).
- Reck, D.J., Axhausen, K.W., 2021. Who uses shared micro-mobility services? Empirical evidence from Zurich, Switzerland. *Transport. Res. Transport Environ.* 94, 102803. <https://doi.org/10.1016/J.TRD.2021.102803>.
- Radzinski, A., Dzięcielski, M., 2021. Exploring the relationship between bike-sharing and public transport in Poznań, Poland. *Transport. Res. Pol. Pract.* 145, 189–202. <https://doi.org/10.1016/j.tra.2021.01.003>.
- Rafiq, R., McNally, M.G., 2021. Heterogeneity in activity-travel patterns of public transit users: an application of latent class analysis. *Transport. Res. Pol. Pract.* 152, 1–18. <https://doi.org/10.1016/j.tra.2021.07.011>.
- Roig-Costa, O., Marquet, O., Arranz-López, A., et al., 2024. Understanding multimodal mobility patterns of micromobility users in urban environments: insights from Barcelona. *Transportation*. <https://doi.org/10.1007/s11116-024-10531-3>.
- Saltykova, K., Ma, X., Yao, L., Kong, H., 2022. Environmental impact assessment of bike-sharing considering the modal shift from public transit. *Transport. Res. Transport Environ.* 105, 103238. <https://doi.org/10.1016/J.TRD.2022.103238>.
- Sopjani, L., Stier, J.J., Hesselgren, M., Ritzén, S., 2020. Shared mobility services versus private car: implications of changes in everyday life. *J. Clean. Prod.* 259, 120845. <https://doi.org/10.1016/J.JCLEPRO.2020.120845>.
- Tassinari, F., 2024. Low emission zones and traffic congestion: evidence from Madrid central. *Transport. Res. Pol. Pract.* 185, 104099. <https://doi.org/10.1016/J.TRA.2024.104099>.
- Teixeira, J.F., Silva, C., Moura e Sá, F., 2021. Empirical evidence on the impacts of bikesharing: a literature review. *Transport. Res. Pol.* 41 (3), 329–351. <https://doi.org/10.1080/01441647.2020.1841328>.
- Tokey, A.I., Alam, M.S., 2023. The travel behavior, attitude, and sociodemographic characteristics of the teleworkers in post-pandemic era. *World Development Sustainability* 2, 100066. <https://doi.org/10.1016/J.WDS.2023.100066>.
- van Mil, J.F., Leferink, T.S., Annema, J.A., van Oort, N., 2021. Insights into factors affecting the combined bicycle-transit mode. *Public Transport* 13 (3), 649–673. <https://doi.org/10.1007/s12469-020-00240-2>.
- Vega-Gonzalo, M., Aguilera-García, Á., Gomez, J., Vassallo, J.M., 2024. Analysing individuals' use of moped-sharing and their perception about future private car dependency. *Cities* 146, 104741. <https://doi.org/10.1016/j.cities.2023.104741>.
- Vermunt, J.K., Magidson, J., 2016. *Upgrade manual for latent GOLD 5.1*. Belmont, MA: Statistical Innovations. Retrieved from. <https://www.statisticalinnovations.com/wp-content/uploads/LG51manual.pdf>. (Accessed 20 February 2025).
- Weschke, J., Oostendorp, R., Hardinghaus, M., 2022. Mode shift, motivational reasons, and impact on emissions of shared e-scooter usage. *Transport. Res. Transport Environ.* 112, 103468. <https://doi.org/10.1016/J.TRD.2022.103468>.
- Zhang, Y., Zhang, Y., 2018. Associations between public transit usage and bikesharing behaviors in the United States. *Sustainability* 10 (6), 1868. <https://doi.org/10.3390/su10061868>.