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Which factors influence the use of shared and privately-owned e-scooters in the city of Madrid? Implications for urban mobility

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Abstract

Micromobility using fully-electric two-wheeled vehicles is increasing in cities worldwide. E-scooters, whether shared or privately-owned, provide short door-to-door trips by facilitating the first/last mile stage of the journey. They are expected to improve livability in cities by reducing harmful emissions and space occupation. In this respect, understanding travel behavior and usage patterns is essential to regulate them appropriately. The purpose of this study is to determine individuals' sociodemographic variables, mobility-related attributes, and latent constructs influencing e-scooter usage. To that end, an individual-level model is estimated to explain the adoption and frequency of use of both shared and private e-scooters based on survey data. The research takes the city of Madrid as a case study, and contributes to a deeper understanding of the differences in the use of privately-owned and shared e-scooters, with a particular focus on the influence of mobility habits and attitudinal variables. The study is complemented with some insights on shared e-scooter usage at the trip-level, which shows the substitution caused on walking trips, and their limited ability to promote modal shifts from the private car. Finally, the research provides valuable implications for urban dynamics and feedback for policymakers and transport planners.

Keywords: E-scooters; E-scooter sharing; Emerging Mobility Services; Urban Mobility; Micromobility; Travel behavior.

1. INTRODUCTION

Urban mobility tends to evolve towards shared mobility (Cohen and Shaheen, 2018), an innovative transportation strategy that enables users to have short-term access to a certain transportation mode (car, e-scooter, bicycle, etc.) on an as-needed basis (Shaheen et al., 2020). This trend towards shared mobility is more evident among young generations (Le Vine and Polak, 2015) and is framed within the advent of the concept of mobility as a service (MaaS), that is, the bundling of different mobility options from multiple providers into a single digital platform for planning, booking, and paying for services (Kamargianni et al., 2016). The adoption of MaaS, in which shared mobility plays an important role, could reduce congestion, parking needs (Falconer et al., 2018), traffic accidents (Warwick et al., 2017), and the carbon footprint of personal mobility in urban areas (Kerttu et al., 2016). Nevertheless, potential regulatory barriers and financial, operational, and social norms might decelerate its success (Polydoropoulou et al., 2020).

Within shared mobility, micromobility includes all services that allow making hybrid use and handling as a pedestrian or a vehicle driven personally at their convenience or when needed (Christoforou et al., 2021). Micromobility vehicles operate at speeds typically below 25km/h (a design speed no higher than 45 km/h) and range from the heaviest two-wheeled self-balancing personal transporters to the smallest lightweight rollers, considering that an approximate weight threshold of around 40 kg (Christoforou et al., 2021). Additionally, micromobility vehicles can be human-powered or motorized, and shared or privately-owned (Christoforou et al., 2021; Fonseca-Cabrera et al., 2021).

Based on the results of a recent survey in the United States and some EU countries, Heineke et al. (2021) concluded that a significant proportion of urban dwellers would be willing to use micromobility for their daily commute. Electric kick scooters, widely known as e-scooters, are one of the most widespread micromobility modes in many cities worldwide (Hosseinzadeh et al., 2021). Furthermore, shared e-scooters are the most widespread shared modality in European urban areas (Fluctuo, 2022). The shared option allows short-term access to an e-scooter on demand rather than having to buy the vehicle, generally subject to payment for using it.

Given the recent growth and prospects for the use of these vehicles, e-scooters are set to play a major role in urban mobility (Younes et al., 2020; Tuncer and Brown, 2020), with important implications for urban livability and sustainability. E-scooters have some positive impacts on urban transportation and sustainability. Christoforou et al. (2021) highlight that these mobility services can potentially contribute to reducing private car use, thus replacing single-occupancy trips and mitigating its related negative externalities such as road congestion. Nevertheless, e-scooters could also have negative impacts on urban mobility, since they may partly substitute active modes and, as a consequence, generate negative effects on the environment (Reck et al., 2021). Additionally, some aspects have been questioned such as the lifespan of the vehicles, especially their electric batteries, the shared use of public space, and their implications for road safety (Tuncer and Brown, 2020; Christoforou et al., 2021). For instance, some contributions such as Fitt and Curl (2019) have analyzed the conflicts between pedestrians and e-scooter users due to the latter riding on the footpath, an environment clearly non-suitable for e-scooter use compared to e.g., bikeways (Zhang et al., 2021). Finally, although shared and privately-owned e-scooters allow users to make similar types of trips, mobility dynamics could vary across users of each type of vehicle, so that urban implications could be different (Tuncer and Brown, 2020; Oostendorp and Hardinghaus, 2022).

Understanding the factors affecting the usage of emerging micromobility systems is essential to identify key implications for transport policy and planning analysis, particularly within a context of rapid changes in urban mobility habits (Esztergár-Kiss et al., 2022), some of them further influenced by the COVID-19 (Nikolaidou et al., 2023). The research works devoted to shared e-scooters have grown exponentially in the past few years, in line with the widespread adoption in many cities worldwide. However, almost no research efforts have been conducted to explore the use of privately-owned e-scooters, nor to analyze differences in their usage patterns compared to the shared option. Previous scientific literature has not addressed the relative influence of using shared e-scooters with the usage of private ones, and vice versa. In this regard, since both alternatives have similarities, it is valuable to jointly consider both these mobility options to understand which factors may impact the adoption and frequency of use of shared and private e-scooters.

From the user behavior perspective, previous scientific literature has mainly focused on examining the impact of sociodemographic variables and activity-travel patterns on e-scooter sharing usage, though the majority was conducted in cities where these services were not available yet (see e.g., Mitra and Hess, 2021; Karlı et al., 2022). Furthermore, a small number of contributions deeply investigated the impact of latent variables when choosing e-scooters, despite their key role evidenced for other micromobility services (see e.g., Muñoz et al., 2016; Márquez et al., 2021). In addition, most of the research studies on e-scooter sharing were conducted before the COVID-19 outbreak, so it has hardly been explored how e-scooter use has been affected by e.g., individuals' fear of COVID-19 contagion or preferences towards private transport modes in the aftermath of COVID-19, as indicated by Christidis et al. (2022) among others. Therefore, further efforts are needed to deeply understand the factors that encourage the use of e-scooters, through a joint analysis covering both private and shared e-scooters, in contexts where these services are already available. Further insight is also needed regarding the impact of e-scooters on demand for traditional modes.

In view of the above, the purpose of this study is to explore the adoption and frequency of use of both private e-scooters and free-floating e-scooter sharing systems. To that end, a survey campaign was conducted in Madrid (Spain), one of the main hubs of shared mobility at the international level given the high supply and variety of such services in operation, especially e-scooter sharing services. This information was exploited to estimate an individual-level model aimed at identifying the key factors (i.e., sociodemographic attributes, mobility-related variables, or psychological preferences and attitudes) determining the usage of e-scooters. Therefore, this research contributes to the scientific knowledge of micromobility by jointly exploring individuals' choices towards both private and shared e-scooters. Additionally, the individual-level model is complemented by some insights into the characteristics of e-scooter sharing trips in the city of Madrid. Our results help understand individuals' e-scooter patterns in the aftermath of COVID-19, being useful for policymakers and transport planners in developing urban policies and planning future infrastructure. At this point, other case studies may find some diverging trends, thereby indicating different e-scooter behavior which could vary from city to city and in time. As pointed out by Gomez et al. (2021), there are distinct differences between cities that may lead to different behaviors.

The remainder of this paper is organized as follows. After this introductory chapter, Section 2 reviews the most relevant body of literature for this research. Section 3 describes the case study considered, the survey campaign managed to capture individuals' use of e-scooters, and the data used for this research through descriptive statistics. Section 4 provides the methodology employed in this study, whereas Section 5 outlines some detailed information on the approach used to build the latent psychological constructs. Section 6 provides modeling results and relevant discussion. Finally, Section 7 presents the overall conclusions, and sets out possible future research steps.

2. LITERATURE REVIEW

The scientific literature on e-scooters has increased noticeably in the past few years, in parallel with the growing penetration of the shared option in many cities. However, the existing knowledge is still limited in certain urban areas, especially when it comes to private e-scooters. This is mainly for two reasons: first, e-scooters are a new micromobility option, so local transportation practitioners and researchers continue to explore patterns of use of e-scooter systems and to learn how the urban environment relates to them; and second, e-scooter datasets are, with some exceptions, limited or unavailable to researchers (Jiao and Bai, 2020).

The majority of contributions in the field of e-scooters have focused on safety-related aspects (see e.g., Yang et al., 2020; Shah et al., 2021; Cicchino et al., 2021; Haworth et al., 2021; Karpinski et al., 2022). Many other publications have explored usage patterns of current shared e-scooter systems at the trip level (see e.g., Jiao and Bai, 2020; Almannaa et al., 2021; Reck et al., 2021; Fauser, 2021; Chicco and Diana, 2022), and the implications of this new urban mobility actor for transport policy and regulation (see e.g., Button et al., 2020; Tuncer and Brown, 2020; Riggs et al., 2021; D'Andreagiovanni et al., 2022). By contrast, relatively few studies have explained the role of individuals' characteristics —e.g., sociodemographic or mobility-related attributes— and underlying factors on e-scooter usage or compared the differences between private and shared e-scooter adoption.

From the travel behavior perspective, the scientific literature on e-scooters can be classified into two main groups: (1) studies focusing on the intention to adopt e-scooters in cities where this service is not available (ex-ante); and (2) studies focusing on urban areas where this service is in operation (ex-post), thus considering data from real users of e-scooters.

Some findings can be highlighted concerning the first set of contributions (**ex-ante studies**). These papers conduct stated preference surveys to analyze factors influencing the intention to adopt e-scooter sharing in different contexts such as Greater Toronto (Mitra and Hess, 2021) or Turkey (Karlı et al., 2022). It is worth mentioning the study by Eccarius and Lu (2020), which used a structural equation analysis to examine the impact of latent psychological variables on the intention to use shared e-scooters. To that end, they surveyed university students in Taiwan and concluded that the perceived compatibility of e-scooters with transportation needs has the greatest effect on the intention to adopt these micromobility vehicles. Interestingly, they observed that environmental consciousness, awareness-knowledge (personal knowledge and attitudes toward electric vehicles), social influence (opinions of familiar people), performance expectancy (whether shared e-scooters would be useful in daily mobility), effort expectancy (easy technology and little effort to use shared e-scooters), and the price of these services are critical factors affecting the usage intention of e-scooter sharing services.

The second set of contributions (**ex-post studies**) considers case studies where e-scooter sharing is already available, so it is possible to capture travel behavior and usage patterns from real users. For instance, it is widely recognized by the scientific literature that e-scooter sharing users tend to be males, young and highly educated people (see e.g., Fitt and Curl, 2019; Laa and Leth, 2020; Javadinasr et al., 2022; Oostendorp and Hardinghaus, 2022). In terms of mode substitution, it has been found that e-scooter trips mainly replace walking, bicycle, and private cars (see e.g., James et al., 2019; Fitt and Curl, 2019; Reck et al., 2022; Oostendorp and Hardinghaus, 2022; Weschke et al., 2022).

Regarding the factors that influence the intention to continue using shared e-scooters, Javadinasr et al. (2022) applied a structural equation model based on survey data in Chicago (US). They identified six latent variables influencing the continuance intention to use e-scooters: perceived ease of use, perceived reliability, perceived enjoyment, variety-seeking lifestyle, perceived usefulness, and social influence. All factors were found to have a positive relationship with the continued use of e-scooters, but the strongest influence was observed for the perceived usefulness of e-scooter sharing in meeting mobility needs.

Other contributions also address the impact of urban environment variables on e-scooter usage. For instance, Jiao and Bai (2020) modeled spatial and temporal patterns of e-scooter trips from April 2018 to February 2019 in Austin (US). They concluded a higher e-scooter usage in areas with higher population density, proximity to the city center, higher density of bus stops or light rail stations, street network connectivity, compact land use, and higher proportion of residents with university studies.

Several authors have focused on exploring the characteristics of e-scooter trips, such as temporal usage patterns and trip purpose, leading to inconclusive results. For instance, Caspi et al. (2020) found that the use of shared e-scooters in Austin is higher on weekends and holidays, while on weekdays their use is higher during off-peak hours. These results suggest that the main trip purpose is other than commuting. Different findings were concluded by Hawa et al. (2021) when analyzing the geo-temporal dynamics of shared e-scooters in Washington D.C. (US). These authors noticed that the average number of shared e-scooters available on weekdays is higher in the afternoon (from 12 p.m. to 6 p.m.), thereby suggesting that they are mainly used for commuting compared to leisure. Interestingly, Wang et al. (2023) have noted that, given the growth of the e-scooter sharing market, trip purposes related to this mobility form will change over time.

The results are also diverse when analyzing e-scooter sharing as first/last mile solutions. For instance, Smith and Schwieterman (2018) analyzed whether shared e-scooters can meet mobility needs in Chicago (US) and pointed out that it is the best cost-benefit alternative for first/last mile transport connections. However, McQueen and Clifton (2022) found that e-scooters are not perceived as a preferred solution to the first/last mile travel by university students from Portland (US).

Of particular interest for the purpose of this research, Laa and Leth (2020) and Oostendorp and Hardinghaus (2022) investigated the socioeconomic profiles and usage patterns associated with both shared and private e-scooters. To the best of our knowledge, these are the only studies that have jointly analyzed users' choices considering private and shared e-scooters. Both studies adopted a descriptive approach to explore patterns associated with e-scooter users: Laa and Leth (2020) in Vienna (Austria), and Oostendorp and Hardinghaus (2022) in Germany. Interestingly, they found that owners present a higher frequency of use than renters. In terms of the gender distribution, they obtained different conclusions. Regarding mode substitution, it was found that shared e-scooters mostly replace walking trips and public transportation, while private e-scooters replace car trips. At the same time, Oostendorp and Hardinghaus (2022) observed some complementarity between e-scooter sharing and public transport.

Finally, some studies have analyzed to what extent the COVID-19 pandemic has affected the use of shared e-scooters. Dias et al. (2022) conducted a systematic literature review to examine the role of shared e-scooters on urban resilience and sustainability during mobility restrictions. From a more quantitative point of view, Hosseinzadeh and Kluger (2021) quantified the impact of the pandemic on shared e-scooters and bikes in Kentucky (US) through a primarily descriptive approach. Interestingly, Li et al. (2020) exploited data at the trip level in Zurich (Switzerland) to explore variations of micromobility behavior before and during the pandemic. Finally, a recent study by Arias-Molinares et al. (2022) examined the impact of the COVID-19 pandemic on the use of shared micromobility services in Madrid. By exploiting data from trip records, these authors found that e-scooter sharing seems to be the most affected shared mobility service with a downfall of 84% from pre-COVID-19 (before March 2020) to COVID-19 times (from March to December 2020). At the same time, trip time decreased by one minute (12.3 vs. 11.3 min) and the average trip distance decreased by 200 meters (2.0 vs. 1.8 km).

Despite the increasing interest in understanding e-scooter use, there are still some gaps in the literature that have motivated this research. As can be noted, there is a need to further explore individuals' choices and preferences toward the use of shared and private e-scooters. The research by Laa and Leth (2020) provides an initial insight of undoubted interest in this field, but analyzing a bigger sample and modeling individuals' behavior are needed to obtain more rigorous conclusions on the factors that might affect the use of private and shared e-scooters. Besides, up to date only a small number of studies have explored the role of latent psychological variables in the use of e-scooters (and particularly in the choice between shared and private ones), although they have been shown to be key in many other contributions on new urban mobility systems, see e.g., Acheampong and Siiba (2020), or Aguilera-García et al. (2022) for carsharing; and Muñoz et al. (2016) or Márquez et al. (2021) for bikesharing. Additionally, most of the research studies in this field have been carried out before the COVID-19 outbreak, so there is a need to study to what extent e-scooter use may have been affected by COVID-related variables such as individuals' fear of COVID-19 infection.

The current study contributes to the existing literature in several aspects. First, it jointly analyzes the influence of multiple explanatory variables (individuals' sociodemographic variables, mobility patterns, and latent psychological constructs) on the use of shared and privately-owned e-scooters, thus leading to a more complete and deeper understanding of the differences in the use of these two mobility forms. This is done by modeling individuals' use of e-scooters through econometric techniques, taking Madrid as a case study. In addition, special attention is paid to the role of psychological variables, which may significantly influence the use of e-scooters. This could be the case of factors such as environmental consciousness or fear of COVID-19 infection since, as indicated by several authors (see e.g., Christidis et al., 2022; Fernández Pozo et al., 2022; Vallejo-Borda et al., 2022), the COVID-19 pandemic has increased individuals' preference for private transport modes.

3. THE DATA: A SURVEY CAMPAIGN IN A EUROPEAN CITY

3.1 Case-study context: the city of Madrid

The city of Madrid, with a total of 3,3 million inhabitants, is the capital of Spain and the second largest city in the European Union after Berlin. Following the traditional European urban standards, Madrid presents a high population density (average values around 9,000 inhab./km^2), particularly in the inner districts (over 24,000 inhab./km^2). The city has a strong social and economic interdependence with numerous surrounding municipalities, all of which form a metropolitan area with more than 6.5 million people. As in other urban areas worldwide, Madrid has experienced an intense development of suburbanization in terms of housing and business activities in recent decades.

Urban mobility in the city of Madrid is characterized by a reasonable balance towards sustainable modes. According to the latest Madrid Mobility Survey (Consorcio Regional de Transportes de Madrid [CRTM], 2020), active modes (walking and biking) account for 34.6% of total trips in the city on a working day, followed by public transport (33.4%) and finally private car/motorbike (28.6%). This modal split in Madrid is partly explained (in line with Feigon et al., 2018) by its high population density and its large supply of public transport options. The public transport system includes one of the longest metro networks at the international level, complemented by an extensive network of urban and suburban bus services, as well as eight suburban rail lines and four tram routes. Despite these sustainable patterns, the city experiences recurrent problems with congestion and air quality (see Romero et al., 2019), with a slightly favorable evolution in the past few years.

The large supply of public transport has been recently complemented by shared mobility options, including services such as carsharing, e-moped sharing, or e-scooter sharing. The high availability of these services has made Madrid one of the main international hubs for shared mobility, as is clearly the case for e-moped sharing (see INVERS GmbH, 2022). As for shared micromobility services, e-scooter sharing is one of the most widely adopted modalities in the city. The first attempt to operate these services in the city took place in 2018, but some problems with licenses forced the local government to put e-scooter sharing on hold until February 2019. By 2020, the City Council granted 4,821 e-scooter licenses but, at the time this research was initiated (2021), more than 7,600 shared e-scooter licenses were active throughout the city, operated by 14 companies. Nevertheless, the number of shared e-scooters actually in operation was very changeable over time and estimated to be significantly lower than the total number of licenses granted. Unfortunately, there has been no official data on the total fleet operated in Madrid by all e-scooter companies. In addition, it was estimated that, as of April 2021, there was a total of 254,000 users of e-scooters (either private or shared ones) in the Region of Madrid (GESOP, 2021).

In the case of Madrid, e-scooters can only be ridden by one person, have no seat or saddle, and are powered exclusively by electric motors which provide a maximum speed of 25 km/h. By law, riding an e-scooter is permitted for people aged above 15, but those under 18 must wear a helmet. In this respect, it is worth noting that e-scooter sharing companies do not accept customers under the age of 18. In Spain, users of these vehicles must ride in the center of the lane, upright and standing. Riding on sidewalks and pedestrian areas is prohibited, but this point is often violated.

E-scooter sharing services are provided throughout the city of Madrid, so even outer areas are served. Each district or neighborhood is assigned a certain number of e-scooters that is somehow related to its population, so that operators must meet these geographic quotas. As seems reasonable, the supply of vehicles and the number of operators is higher in inner (and denser) neighborhoods, but operators must serve the outer areas even if it is sometimes not profitable for them. Given the low profitability and high competition, some companies have recently withdrawn from the market. Furthermore, the local government is considering launching a concession for three operators and imposing a fleet cap on shared e-scooters.

The information shown in Table 1 characterizes e-scooter sharing for the main operators providing these services in Madrid by mid-2021. Charges are mostly established on a per-min basis, but some companies set charges on an hourly basis (see the case of Scoot in Table 1). Some operators also apply an additional charge (typically 1 Euro) for unlocking the e-scooter. The approximate average price for renting an e-scooter is 0.15 Euros per minute, with prices ranging from 0.11 to 0.23 Euros per minute. Shared e-scooters in Madrid are free-floating and can be parked on the sidewalk, except in pedestrian streets or where there are specific parking spaces for these vehicles (e.g., stations and anchorages specifically reserved for this purpose on sidewalks and parking areas) within 50 meters.

Table 1. Characterization of e-scooter sharing services for the main operators in Madrid (2021)

Operator	Lime	Taxify	Scoot	Voi	Acciona
Implementation	2018	2018	2018	2018	2018
No. e-scooters	641	750	309	162	179
No. Districts operated (out of a total of 21)	15	17	14	10	11
Unlocking fee	0 Euro	1 Euro	0 Euro	1 Euro	0 Euro
Price	0,15 Euro/min	0,15 Euro/min	10 Euros per 1 h; 15 Euro per 2 h; 20 Euros per 3 h	0,15 Euro/min	0,23 Euro/min

Like many other cities around the world, Madrid experienced a special situation with respect to COVID-19 infection in recent years. As a result of lockdowns and mobility restrictions, Madrid experienced a rapid decrease in mobility rates, especially during the first lockdown[1]. Additionally, the usage of private transport was very high compared to public transport (Akioui Sanz et al., 2021; Radics and Christidis, 2022).

As indicated below in Section 3.2, the data employed in this research were collected in May-July, 2021, a period when mobility restrictions were no longer effective, but when the COVID-19 pandemic was still quite active. Two main waves of infection were observed prior to this research, from September to November 2020 and January to mid-March 2021. The widespread vaccination of the population, which started in Spain in April 2021, led to a significant drop in infections and their severity. As of May-July 2021, when the data for this research was

[1] During the first lockdown (March-June 2020), trips made in the Region of Madrid fell by 70% compared to pre-COVID levels, considering that only essential travel was allowed. After that hard lockdown was lifted, trips by both private and transit trips in the Region of Madrid sharply increased by more than 60% compared to the lockdown levels.

collected, the daily average (7-day average) did not exceed 2,000 infections (30 infections/100,000 inhab.), with cumulative incidence rates under 228/100,000 inhab. However, some noticeable waves of infection were observed in the following months, especially during the summer holidays (August 2021). In addition, the pandemic has brought significant changes in individual behavior, greatly impacting trip demand and distribution (Arias-Molinares et al., 2022; Christidis et al., 2022). For instance, public transport was still underperforming and teleworking levels were higher compared to the pre-pandemic situation in major Spanish cities (Akioui Sanz et al., 2021; Radics and Christidis, 2022).

3.2 Data collection and survey design

A specific survey campaign on e-scooter usage was conducted in Madrid in 2021. Existing data potentially useful for this research and already available was not considered appropriate for the purpose of this investigation, as is the case of e.g., the latest Madrid mobility survey in 2018 (see CRTM, 2020). Given the still minor presence of e-scooters in urban modal share, this source captured very few e-scooter users and consequently provided scarce insight into micromobility usage. Therefore, it was needed to design a specific survey to achieve the objectives of the study to capture the main determinants that influence the use of e-scooters, both privately-owned and shared ones.

The target population in this study comprises those people of legal age (people aged 18 years and above), residing in and/or commuting to the city of Madrid, who are aware of the existence of e-scooter sharing services and/or private e-scooters. The survey was designed after developing a comprehensive review of previous questionnaires on individuals' willingness to use and/or adopt micromobility services (e.g., Munkácsy, 2017; Mitra and Hess, 2021). The final questionnaire was defined after a pilot survey conducted by the authors. Several screening questions were included in the questionnaire to exclude respondents who do not meet certain requirements, such as residing outside the Madrid metropolitan area or not knowing about the existence of e-scooters (shared and/or private).

The survey campaign was conducted from May to July 2021, avoiding summer break, holidays, or special events, in order to collect fairly representative data on urban mobility patterns in Madrid. Online questionnaires were considered the most appropriate approach for collecting the information for this study for several reasons. First, this methodology enabled capturing answers in difficult public-health situations due to the COVID-19 pandemic. Second, web-based questionnaires have been widely used in similar studies on shared mobility (see e.g., Mitra and Hess, 2021; Gomez et al., 2021; Julio and Monzon, 2022), providing good data quality with a reasonable economic effort. The web-based survey was disseminated through multiple sources such as messaging apps, banner ads, social media platforms, and electronic mailing lists. The initial sample size was 768 responses, but the final database was reduced after excluding incomplete answers, and removing those observations including inconsistent or non-logical answers. Consequently, the complete dataset for this study consisted of 694 valid responses.

The survey captured four main aspects from respondents:

- *Individuals' sociodemographic characteristics*: gender, age, level of education, household annual income, occupation, household structure, and residential location based on zip codes.

- *Usual mobility habits and travel-related information:* public transport card ownership, vehicle ownership (including car, motorcycle, e-bike, and e-scooter), number of trips on the last weekday and non-weekday (excluding walking trips), and number of walking trips over 10 minutes on the last weekday and non-weekday.

- *Lifestyle preferences and attitudinal statements*: respondents were asked to rate their level of agreement, on a 5-point Likert scale, towards 21 different statements on multiple topics. The attitudinal statements covered the following individuals' behaviors, preferences, habits, and perceptions:

  i) Environmental consciousness. Environmentally friendly behavior concerning the mode of transport chosen, waste recycling efforts, and willingness to pay more for environmentally friendly products, were captured by several indicators. In this respect, pro-environmental attitudes may lead to greater usage of environmentally friendly modes of transport (such as electric shared vehicles, public transport, and bicycles) instead of private fossil fuel vehicles, as already found in the literature (see e.g., Astroza et al., 2017; Acheampong and Siiba, 2020; Julio and Monzon, 2022).

  ii) Tech-savviness. Several indicators captured the interest of the individuals regarding new technologies, such as online social media, internet services, or mobile apps for daily tasks. This latent construct has been widely used in previous research studies exploring the usage of emerging urban transportation modes, such as carsharing (see e.g., Velázquez Romera, 2019; Acheampong and Siiba, 2020; Aguilera-García et al., 2022).

  iii) Physical agility. A set of basic physical attributes measures the capacity of the individuals to ride a bicycle and climb stairs, slopes, etc. The inclusion of this construct is reasonable since a relatively good physical condition seems to be an important factor when riding a micromobility vehicle (Muñoz et al., 2013).

  iv) Willingness to share. Individuals' willingness to purchase second-hand products, along with the tendency to use sharing economy apps or websites (as is the case of e-scooter sharing), was captured by several indicators. This construct may potentially influence e-scooter sharing use, as also suggested for other shared mobility options in the Spanish context (see e.g., Velázquez Romera, 2019; Gomez et al., 2021; Aguilera-García et al., 2022). Additionally, our latent construct is also connected with new technologies and disruptive practices, which also could affect the usage of shared mobility options.

  v) Preventive COVID-19 infection behavior. A set of indicators highlight the personal susceptibility and sensitivity to COVID-19. The inclusion of this latent construct is deemed noteworthy given that the COVID-19 pandemic has led to drastic changes in individuals' mobility behavior (see e.g., Shamshiripour et al., 2020; de Haas et al., 2020; Christidis et al., 2022; Fernández Pozo et al., 2022; Nikolaidou et al., 2023), such as a modal shift from public transport to private vehicles.

  vi) Safety awareness. Several indicators capture individuals' safety awareness as a pedestrian and/or as a rider of different modes of transport (car, moto, bike), along with perceptions of occupational risk prevention measures. Given the vulnerability of e-scooter riders versus e.g. car drivers when riding on the street, the inclusion of this latent construct in our behavioral model makes sense. Individuals' perceptions of safety factors and risk aversion may potentially affect the use of micromobility vehicles, as also revealed in the case of cycling (see e.g., Muñoz et al., 2016; Márquez et al., 2021 or Julio and Monzon, 2022).

vii) Perceived availability of shared e-scooters. A set of statements addresses the perceived and subjective availability of e-scooter sharing services. Even though the presence of shared e-scooters is somewhat evident throughout Madrid city, adoption or usage may be influenced by the subjective identification of shared e-scooters circulating or parked around the city. Additionally, the degree to which people trust in e-scooter sharing services depends on the availability of e-scooters at times and in places they are needed, as indicated by Javadinasr et al. (2022).

- *Usage of e-scooters*: respondents reported their adoption and frequency of use of e-scooters, both private and free-floating e-scooter sharing services (see more details in Section 3.3). These are the main variables of interest modeled in this study. For a better understanding of mobility trends related to e-scooter sharing, respondents were asked to report details about their last trip in a shared e-scooter, including trip purpose, day of the week, time of day, travel time, complementarity with other modes of transport in the same trip, and the mode of transport that would have been used if no shared e-scooter had been available.

To provide a clearer description of the survey content, it has been presented in four defined blocks, as described above. Nevertheless, it is important to mention that sociodemographic-related questions were presented at the end of the survey, and the battery of attitudinal statements was mixed throughout the questionnaire, as suggested in the survey design literature. Researchers carefully took all the actions needed to comply with the provisions of current legislation on the anonymity and protection of personal data[2].

The basic descriptive statistics of the socioeconomic, demographic, and activity-travel variables are detailed in Section 3.3. In order to complement the modeling results, Section 3.4 provides some insights into the use of e-scooter sharing systems at the trip level.

3.3 Data description

In the survey, respondents were asked to report their frequency of use of e-scooters, both private and shared free-floating, among the following categories: i) I have never used it; ii) I last used it some months ago; iii) I use it less than once a month; iv) I use it 1-4 times a month; and v) I use it every week.

This information has been used to build the main four variables of interest in our model, capturing the adoption and frequency of use of shared and private e-scooters. Adoption variables are represented as binary variables indicating whether the individual has ever used each mobility option, while the variables for frequency of use were considered to be built with the following four categories: (1) *infrequent* (last used some months ago); (2) *occasional* (used

[2] Appropriate informed consent and research permissions were obtained, and the data collected have been kept confidential. Although sensitive data were asked from respondents (e.g., gender, age, level of income, etc.), the questionnaire did not collect personal information (e.g., name, ID, residential address, etc.). Additionally, this paper only provides aggregated statistical information and modeling results to ensure that sensitive data is not disclosed.

less than once a month); (3) *monthly* (used 1-4 times a month); and (4) *weekly* (used every week).

Table 2 summarizes the distribution of the usage of both mobility options in the dataset. According to the results, e-scooter sharing adoption (39.8%) is considerably higher compared to the usage of privately-owned e-scooters (15.9%). By comparison, Fitt and Curl (2019) indicated that only 18% of respondents had used privately-owned e-scooters. However, riders of private e-scooters seem to make a more regular and frequent use (see Table 2), as also indicated by Laa and Leth (2020), and Oostendorp and Hardinghaus (2022). Interestingly, 65 out of 110 users of private e-scooters reported that they had also used the shared option at some point.

Table 2. Usage (adoption and frequency of use) of shared and private e-scooters in the complete dataset (n = 694)

Usage	Shared e-scooters		Private e-scooters	
	Respondents	% Sample	Respondents	% Sample
Non-user (never used)	418	60.23	584	84.15
Infrequent (last used some months ago)[a]	60	8.65	58	8.36
Occasional (less than once a month)[a]	127	18.30	5	0.72
Monthly (1-4 times a month)[a]	65	9.37	9	1.30
Weekly (1 or more times a week)[a]	24	3.46	38	5.48
Total	694	100.00	694	100.00

[a] In the modeling estimation of the frequency of use of private e-scooters, this variable was merged with the following two categories: (1) infrequent/occasional (used less than once a month) with 63 out of 110 users; and (2) monthly/weekly (used more than once a month) with 47 out of 110 users. The reader is referred to Section 4 for further details.

Table 3 shows the distribution of explanatory variables in the complete dataset. Different groupings within the categorical variables were tested to ensure good representativity and later identify the factors most strongly related to the usage of e-scooters. It is important to remind that people who did not express their awareness of the existence of e-scooters (private or shared) were screened out of the survey. Therefore, the complete dataset is not necessarily representative of the entire population residing in and/or commuting to Madrid, which does not affect the validity of the sample for the type of analysis conducted in this research[3] (see Wooldridge, 1999 and Solon et al., 2015). For comparative purposes, the values available from official statistics (see Madrid City Council, 2021) are provided insofar as it is possible for the sociodemographic variables (people aged 18 years and above) of the city of Madrid. However, this comparison is quite complex to conduct and not totally fair, given that the targeted population of this research is expected to be very different from the total population of Madrid. In fact, the sample presents some over-representation of young and middle-young individuals, which seems reasonable given the data collection method and the greater awareness of shared mobility services among this segment of the population.

[3] It should be noted that the focus of the current paper is not so much on obtaining a perfect representativeness of the target population as it is on estimating causal effects, i.e., how changes in exogenous factors impact the endogenous variables of interest. This requires obtaining sufficient heterogeneity and subgroup sample sizes to have precise estimates and adequately detect causal relationships and patterns in the data from the statistical models.

Table 3. Summary of explanatory variables in the complete dataset

VARIABLES	Subgroup	Respondents	% Sample	*% Official Data 2021*
SOCIODEMOGRAPHIC ATTRIBUTES				
Gender	Male	414	59.7%	*45.8%*
	Female	280	40.4%	*54.2%*
Age	18-19	88	12.7%	*2.2%*
	20-24	248	35.7%	*6.1%*
	25-34	166	23.9%	*16.1%*
	35-49	131	18.9%	*27.6%*
	50 or more	61	8.8%	*48.1%*
Education	Secondary education or lower	255	36.7%	*62.3%*
	Bachelor's degree(s)	195	28.1%	*7.4%*
	Graduate degree(s) (e.g., MS, PhD)	243	35.0%	*30.2%*
	DN/DWA	1	0.1%	*0.1%*
Annual HH income	Less than 18,000 Euro	71	10.2%	
	18,000 to 29,999 Euro	106	15.3%	
	30,000 to 59,999 Euro	135	19.5%	
	60,000 Euro or more	102	14.7%	
	Without own income	158	22.8%	
	DN/DWA	122	17.6%	
Occupation	Student	277	39.9%	
	Employed	210	30.3%	
	Part-time employee/student	133	19.2%	
	Other (homemaker, unemployed, retired, etc.)	74	10.7%	
Household structure	Living alone	38	5.5%	
	Living with non-relatives (e.g., roommates)	64	9.2%	
	Couple without children	78	11.2%	
	Family with children	510	73.5%	
	Other types of family	4	0.6%	
Residential location	Madrid city: inside the M30 Ring	212	30.6%	
	Madrid city: outside the M30 Ring	241	34.7%	
	Metropolitan area (outside Madrid city)	195	28.1%	
	DN/DWA	46	6.6%	
MOBILITY-RELATED ATTRIBUTES				
Public transport card ownership	No	150	21.6%	
	Multi-personal reloadable card (10-journey and single ticket)	161	23.2%	
	Monthly/Annual season ticket	383	55.2%	
Vehicle ownership	No	151	21.8%	
	Regular access to a vehicle	543	78.2%	
E-bike ownership	No	433	62.4%	
	Regular access to an e-bike	261	37.6%	
E-scooter ownership	No	592	85.3%	
	Regular access to an e-scooter	102	14.7%	
Weekday mobility (excluding walking trips)	Zero trips	66	9.5%	
	1 to 2 trips	436	62.8%	
	3 or more trips	192	27.7%	
Non-weekday mobility (excluding walking trips)	Zero trips	120	17.3%	
	1 to 2 trips	351	50.6%	
	3 or more trips	223	32.1%	
Weekday walking trips over 10 min	Zero trips	149	21.5%	
	1 to 2 trips	383	55.2%	
	3 or more trips	162	23.3%	
Non-weekday walking trips over 10 min	Zero trips	124	17.9%	
	1 to 2 trips	301	43.4%	
	3 or more trips	269	38.8%	

As can be observed in Table 3, the sample has sufficient sociodemographic variability. The sample presents a higher proportion of males (59.7%) and individuals aged under 35 (72.3%). There is also a noticeable presence of highly educated people, with 63.1% of respondents having university studies, while household income is fairly evenly distributed. Concerning occupation, 39.9% of respondents are students, 30.3% are employees, and 19.2% are part-time employees/students. As for household structure, families with children make up the majority of the sample (73.5%). These sample characteristics are in line with many aforementioned studies on emerging urban mobility services (see e.g., Munkácsy and Monzon, 2018; Wang et al., 2018; Gomez et al., 2021), particularly if we take into account that gender and age gap is the most noticeable sociodemographic characteristic in terms of interest in and use of micromobility services (see e.g., Degele et al., 2018; Nikiforiadis et al., 2021; Mitra and Hess, 2021; Javadinasr et al., 2022).

Most respondents live in Madrid city, 30.6% of them inside the first ring road M30 and 34.7% outside the M30. The remainder 28% of respondents live beyond the municipal limits of Madrid but within the metropolitan area and commute to the city of Madrid. Concerning travel-related information, most respondents have a public transport card, either a monthly/annual (55.2%) or a multi-personal reloadable (23.2%) transit card; and there is a noticeable share of individuals in the sample with regular access to a vehicle (car/moto) in their household (78.2%). Ownership or access to an e-bike or an e-scooter presents a lower proportion (37.6% and 14.7, respectively), as could be expected. Finally, the distribution indicates slightly higher mobility rates (excluding walking trips) during weekdays compared to non-weekday mobility, while the opposite is found for walking trips over 10 min.

The information presented in Appendix A shows the distribution of explanatory variables across e-scooter adoption (either private or shared). This point is of great interest to explore, at least preliminarily, differences between users and non-users of shared and private e-scooters in terms of the distribution of all potential explanatory variables. According to the results, gender, age, education, and occupation seem critical variables impacting the use of e-scooter sharing. There is a higher presence of males than females within the group of shared e-scooter users. The proportion of adopters is also higher among young people and students. Concerning the level of education, we can observe a higher share of adopters with a Bachelor's degree across shared e-scooter users compared to the complete dataset. Furthermore, we can observe that e-scooter sharing services are more highly adopted by respondents living with non-relative members or roommates, which is also related to young people and students. It is also found that living in the city center could be related to a greater adoption of e-scooter sharing services, which can be explained by the fact that the supply of these services is greater in denser urban districts. Likewise, the use of e-scooter sharing seems to be higher among those people who declared not having regular access to a private vehicle and/or an e-bike, and those individuals frequently using public transport. Finally, shared e-scooter adopters show a somewhat higher intensity in their out-of-home activity (higher weekend mobility rates).

As for private e-scooters, some differences can be found in this preliminary analysis. Age does not seem to influence the probability of adoption. Additionally, it is observed that the use of private e-scooters is higher among respondents living in Madrid city, which is not only limited to residents of the city center as was previously the case with the shared option. The most interesting trend is the influence of the usage of public transportation. In this respect, according to Appendix A, it seems that private e-scooter adopters are low-intensive users of public transport, while a complementarity effect with vehicle ownership is suggested.

It is worth noting that all of the above comments are of great interest but can only be considered preliminary insights, and more rigorous techniques are needed to draw more conclusive results on the use of shared and private e-scooters.

3.4 Insights on the use of e-scooter sharing systems at the trip-level

This section complements the individual-level model by exploring e-scooter sharing mobility patterns at the trip level in the city of Madrid. Specifically, it characterizes e-scooter sharing demand, providing insights into the mobility trend of this service at the trip-level. To that end, we exploit the information on the last e-scooter sharing trip provided by those users who declared remembering that trip (n = 239; 86.6% of adopters of shared e-scooters in the sample). This information is particularly relevant in the context of rapid changes due to, among other things, the COVID-19 pandemic and before a fleet cap on e-scooters is imposed in Madrid. Additionally, it is important to note that the information on the last private e-scooter trip is not representative enough, so we decided not to use it for this paper. We did not obtain enough representativeness because: first, private e-scooter adoption seems to be low (15.9%); and second, with the aim of avoiding an excessive amount of time for completing the questionnaire, those people who adopted both shared and private e-scooters were asked to report only on the last trip (either by shared or private e-scooter) they remembered.

Table 4 includes descriptive characteristics for the trips by shared e-scooters reported in the subsample. This data includes multiple trip-related attributes such as trip purpose, day of the week, time of day, travel time, complementarity with other modes of transport in this specific trip, and the mode that would have been used if the shared e-scooter had not been available. As one might expect, this information should be taken with caution because it is difficult to disentangle whether the choices made for the last e-scooter sharing trip are a snapshot of a specific choice or simply a reflection of the overall activity-travel pattern of the individual. Thus, this approach is intrinsically exploratory, considering characteristics of an isolated trip outside the broader context of the individual's mobility patterns.

As can be noted, the most common trip purpose is by far leisure (51.5%), followed by work-related trips (18.8%), that is, commuting to the workplace or education center/university. These insights into trip purposes are also aligned with other research works such as McKenzie, G. (2019), Caspi et al., (2020), Oostendorp and Hardinghaus (2022), and Arias-Molinares et al. (2022). Remarkably, 15.5% of respondents reported having used the shared e-scooter just to try the service, denoting that it is still an emerging urban transportation mode. In terms of time-dependent patterns, a higher share of trips has been made during weekends, late evenings, and night periods, which again is also connected with leisure activities, the most common trip purpose reported above. Along the same line, other studies (Bai and Jiao, 2020; Caspi et al., 2020) found greater e-scooter sharing ridership on weekends. Additionally, Bai and Jiao (2020), Reck, et al. (2021) and Arias-Molinares et al. (2022) also observed that the use of shared e-scooters is higher in the afternoons and evenings. By contrast, Hawa et al. (2021) suggested that e-scooter sharing is mainly used during weekdays in the case of Washington D.C. (US).

On the travel time dimension, it seems that e-scooter sharing systems are mainly covering short-distance mobility needs, given that the majority of trips are under 15 minutes, whereas only 15.5% are over 20 minutes. This finding is also supported by previous research studies, which indicate an average trip time of 7.5 minutes in Austin (Jiao and Bai, 2020), 11.3 minutes in Madrid (Arias-Molinares et al., 2022), and 16 minutes in Germany (Oostendorp and Hardinghaus, 2022). In this regard, we can confirm that e-scooters are of special interest for short-distance trips in urban settings.

Table 4. Trip characteristics of the last trip in a shared e-scooter

VARIABLES		Trips (n = 239)	% Sample
Trip purpose	Leisure/social or recreational activity	123	51.5%
	Commuting to the workplace or education center/university	45	18.8%
	Attending a work meeting (outside my workplace)	1	0.4%
	Shopping, personal or family errands	26	10.9%
	Trying an e-scooter sharing service	37	15.5%
	Other	7	2.9%
Day of week	Monday-Thursday	80	33.5%
	Friday	31	13.0%
	Saturday-Sunday	101	42.3%
	DN/DWA	27	11.3%
Time of day	6:00 – 13:00	34	14.2%
	13:00 – 17:00	34	14.2%
	17:00 – 21:00	91	38.1%
	21:00 – 2:00	45	18.8%
	2:00 – 6:00	12	5.0%
	DN/DWA	23	9.6%
Travel time	Less than 5 minutes	22	9.2%
	Between 5 and 10 minutes	75	31.4%
	Between 10 and 15 minutes	66	27.6%
	Between 15 and 20 minutes	33	13.8%
	More than 20 minutes	37	15.5%
	DN/DWA	6	2.5%
Complementarity with other modes	Public transport: metro, bus, train, commuter rail, etc.	61	25.5%
	My own vehicle	17	7.1%
	Other shared mobility options (carsharing, moped sharing, bikesharing)	7	2.9%
	No	154	64.4%
Mode substituted	Walking	135	56.5%
	Public transit: metro, bus, train, commuter rail, etc.	44	18.4%
	My own vehicle	5	2.1%
	My own e-scooter or bicycle	3	1.3%
	Other shared mobility options (carsharing, moped sharing, bikesharing)	29	12.1%
	Taxi or ridehailing	14	5.9%
	Other	9	3.8%

Furthermore, we explore the complementarity with other modes of transport, that is, those modes from which users are switching to/from a shared e-scooter. Most e-scooter trips involve only one stage (64.4%), so no combination with existing transport modes is observed for the majority of cases. Nevertheless, there is some complementarity between e-scooter sharing and public transport (25.5%), increasing its efficiency and attractiveness. In this regard, Oostendorp and Hardinghaus (2022) also observed that nearly a quarter of shared e-scooters trips are combined with public transport.

Finally, from descriptive statistics, there is evidence that shared e-scooters have mainly substituted walking trips. In this regard, 56.5% of the trips would have been made on foot in case e-scooter sharing had not been available. This is followed by public transportation (18.4%) and, to a lesser extent, other shared mobility options (12.1%). This finding is aligned with other research on shared e-scooters (see e.g., James et al., 2019; Fitt and Curl, 2019; Laa and Leth, 2020; Mitra and Hess, 2021; Nikiforiadis et al., 2021; Oostendorp and Hardinghaus, 2022; Javadinasr et al., 2022; Reck et al., 2022; Weschke et al., 2022). Considering the results, the idea that car trips are barely substituted by e-scooter sharing seems to be reinforced, so the positive impacts of e-scooter sharing on the environment happen to be questionable.

4. METHODOLOGY

This research explores the key variables (socioeconomic, psychological constructs, mobility habits, etc.) determining the usage of e-scooters at the individual level. To that end, the methodology adopts highly advanced econometric techniques in the framework of choice modeling, based on the data collected from a survey campaign. As commented above, the sample size consisted of 694 valid responses, which is used in all the modeling estimations, except for the final submodels on the frequency of use (276 and 110 individuals make up the subsamples of e-scooter sharing and private e-scooters, respectively).

Particularly, we estimate a choice model based on the utility-maximizing framework (see e.g., Ben-Akiva et al., 2002) at the individual level, in which we integrate latent behavioral constructs and include multi-stage interrelations between variables. Within the choice modeling framework, we used the statistical technique of Generalized Structural Equation Modeling (GSEM), since this approach provides a flexible tool to easily analyze the interrelations between variables, study complex choice processes, incorporate successive interrelationships between endogenous variables, accommodate cause-effect structures, and include multiple linking functions of different nature (Rabe-Hesketh et al., 2004). The standard calibration method is the maximum likelihood estimation. An in-depth explanation of the GSEM technique, as well as its estimation process, is beyond the scope of this article so the reader is referred to Rabe-Hesketh et al. (2004) and Bartus (2017). It is worth noting that GSEM-based analyses have been widely adopted in previous studies in the field of transport research (see e.g., Yin et al., 2020; Vega-Gonzalo et al., 2023).

Prior to estimating the aforementioned model, we built the unobserved latent constructs from the responses to the 21 attitudinal statements (indicators) captured in the questionnaire on different topics. To that end, an Exploratory Factor Analysis (EFA) was conducted to extract the optimum latent variables (factors) that sufficiently account for the covariance patterns among them. The EFA suggested seven factors for the indicators collected in the survey: environmental consciousness, tech savviness, physical agility, willingness to share, preventive COVID-19 infection behavior, safety awareness, and perceived availability of shared e-scooters. This was subsequently confirmed by the Confirmatory Factor Analysis (CFA). Section 5 presents further details of the indicators employed, their internal consistency, the seven unobserved latent constructs obtained, the validity of the postulated structure, and the results of the statistics in the CFA framework.

After defining the latent constructs, we jointly estimate the measurement variables and choice outcomes using a GSEM-based analysis, which integrates the latent constructs and represents multi-stage interrelations between variables as explained below. An overview of the individual-level model adopted to explain the usage of both shared and private e-scooters is presented in Figure 1. Firstly, in the SEM part, the latent constructs are defined as functions of individuals' sociodemographic factors. These relationships are estimated through observations of the latent construct indicators since a parsimonious dependence structure through the stochastic latent constructs is established. Then, we simultaneously preserve the correlation among measurement variables by extracting the seven optimum latent variables (see more comments in Section 5), which can explain the common variances in the measurement variables. Furthermore, both the underlying latent constructs and the exogenous variables are incorporated as determinants of all endogenous outcome variables of interest in this research:

mobility rates and walking trips on the last weekday and non-weekday, and especially, adoption and frequency of use of e-scooters (shared and private ones).

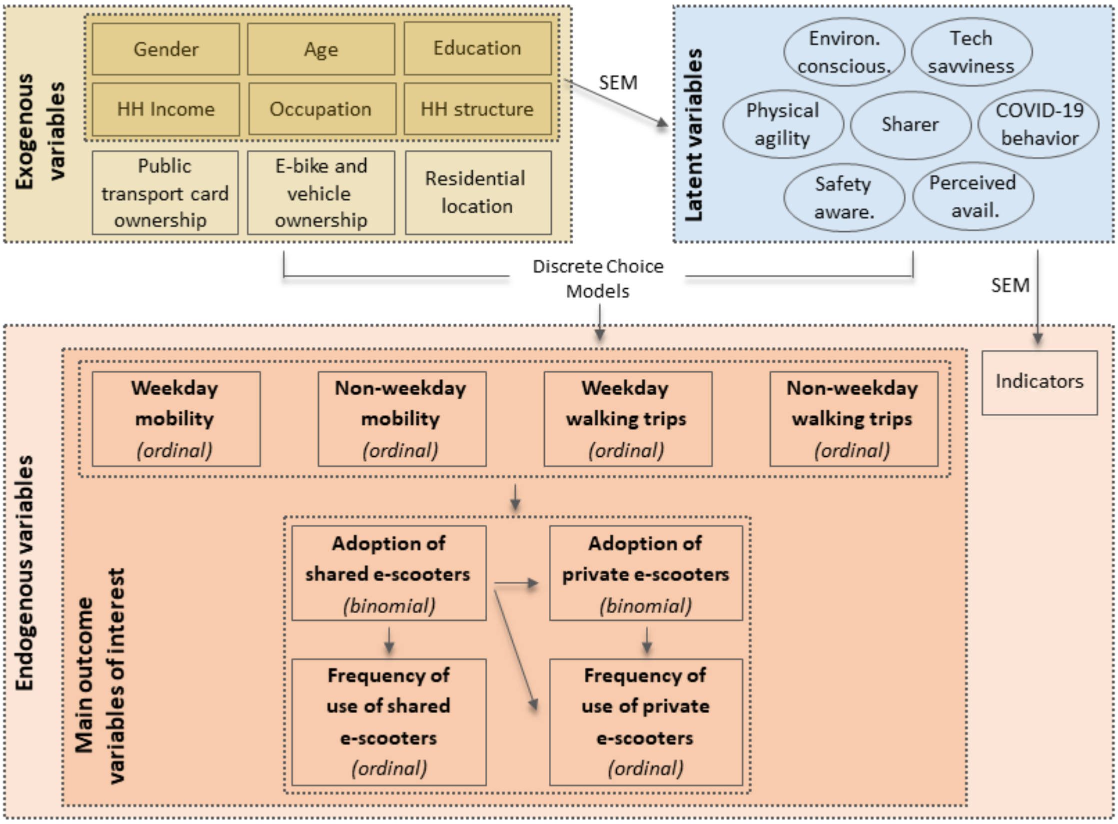

Figure 1. Structure of the individual-level model to explore the usage of both shared and private e-scooters

As can be observed in Figure 1, the endogenous variables are modeled in a sequential manner by employing different link functions (ordinal and binomial logit) depending on the nature of each dependent variable. The sequential structure adopted in the individual-level model is aimed at explaining the usage of both shared and private e-scooters, controlling for potential self-selection effects, and accommodating recursive effects among variables. After testing multiple recursive directionalities between endogenous variables, the best fitting model was obtained in the causal specification assuming both mobility rates and walking trips (on the last weekday and non-weekday) impacting the adoption of shared and private e-scooters, and all the above endogenous variables finally influencing the frequency of use. Therefore, the adoption variables control for the potential self-selection effect coming from non-users of each mobility option. Additionally, the adoption of shared e-scooter sharing is assumed to impact both the adoption and frequency of use of private e-scooters. Consequently, the current study also holds insights into how e-scooter sharing attitudes influence the usage of private e-scooters, which has been crucial in previous research on other micromobility services (see for example Julio and Monzon, 2022 for the case of bikesharing in Madrid).

Finally, it is important to mention that, although our data on the frequency of use of private e-scooters are fairly in line with previous research (see e.g., Fitt and Curl, 2019; Laa and Leth, 2020; Oostendorp and Hardinghaus, 2022), the number of observations in certain categories is low for the purpose of modeling (see Table 2). In this regard, different groupings within the categories were tested to ensure good representativity and thorough application of the GSEM-based analysis. Consequently, the variable for frequency of use of private e-scooters was merged with the following two categories: (1) infrequent/occasional (used less than once a month) with 63 out of 110 users; and (2) monthly/weekly (used more than once a month) with 47 out of 110 users.

5. LATENT VARIABLES CONSTRUCTS

Respondents were asked in the questionnaire to report their level of agreement about 21 attitude statements on different topics (see Figure 2), which represent the indicators employed to later build the underlying latent constructs included in our model. A Likert-type scale ranging from 1 (completely unidentified) to 5 (completely identified) was the scoring system used to measure the attitudinal behavior of the individuals. Thus, the current study holds insights into how different individual attitudes and preferences influence the usage of e-scooters, which have been crucial in previous research on other emerging mobility services such as ridehailing or carsharing. Following recommendations in the survey literature, these statements were not designed in a homogeneous way and were mixed throughout the questionnaire to mitigate automatic responses by individuals and include adequate heterogeneity in each latent construct. Based on these statements, an EFA was conducted to specify the optimal number of latent constructs that sufficiently account for the covariance patterns among them. After testing different numbers of orthogonal and oblique rotations, an EFA with oblique Promax rotation was used in this research, making the solution more interpretable. Additionally, a factor loading value of 0.50 was laid down as the threshold to maintain an indicator within a factor. This value indicates the relationship of each indicator with the latent constructs, i.e., the strength of each indicator on a factor and its direction.

The EFA suggested seven latent factors for the 21 indicators. Then, we used CFA to test the specific theoretical hypothesis about the data obtained with the EFA. Therefore, making the prior assumption obtained in the EFA, we validated the structure across observed indicators and latent variables according to the literature (Akaike, 1987; Hu and Bentler, 1999; Kline, 2016).

Figure 2 presents the statements obtained in each underlying latent construct according to the EFA and CFA results, and the attitudinal statement loadings obtained with the EFA, which were as expected. It is important to note that two statements were removed as they did not load well on any of the factors and obtained a factor loading lower than 0.50. As a result, 19 attitudinal statements were finally kept.

Factor 1 (FA1) captures the pro-environmental attitudes of the individuals with three indicators. Factor 2 (FA2) is made up of three statements that reflect the familiarity of individuals with new technologies. Factor 3 (FA3) measures the ability of individuals to ride a bicycle and climb stairs, slopes, etc. Factor 4 (FA4) is related to individuals' willingness to purchase second-hand products, along with the tendency to use sharing economy apps or websites. Factor 5 (FA5) is associated with four indicators and refers to the personal susceptibility and sensitivity to COVID-19. Factor 6 (FA6) captures individuals' perceptions of safety factors and risk aversion through three indicators. Finally, Factor 7 (FA7) measures the perceived and subjective availability of e-scooter sharing services. As a result, we constructed 7 latent variables, denominated "Environmental consciousness" (FA1), "Tech-savviness" (FA2), "Physical agility" (FA3), "Willingness to share" (FA4), "Preventive COVID-19 infection behavior" (FA5), "Safety awareness" (FA6), and "Perceived availability of shared e-scooters" (FA7).

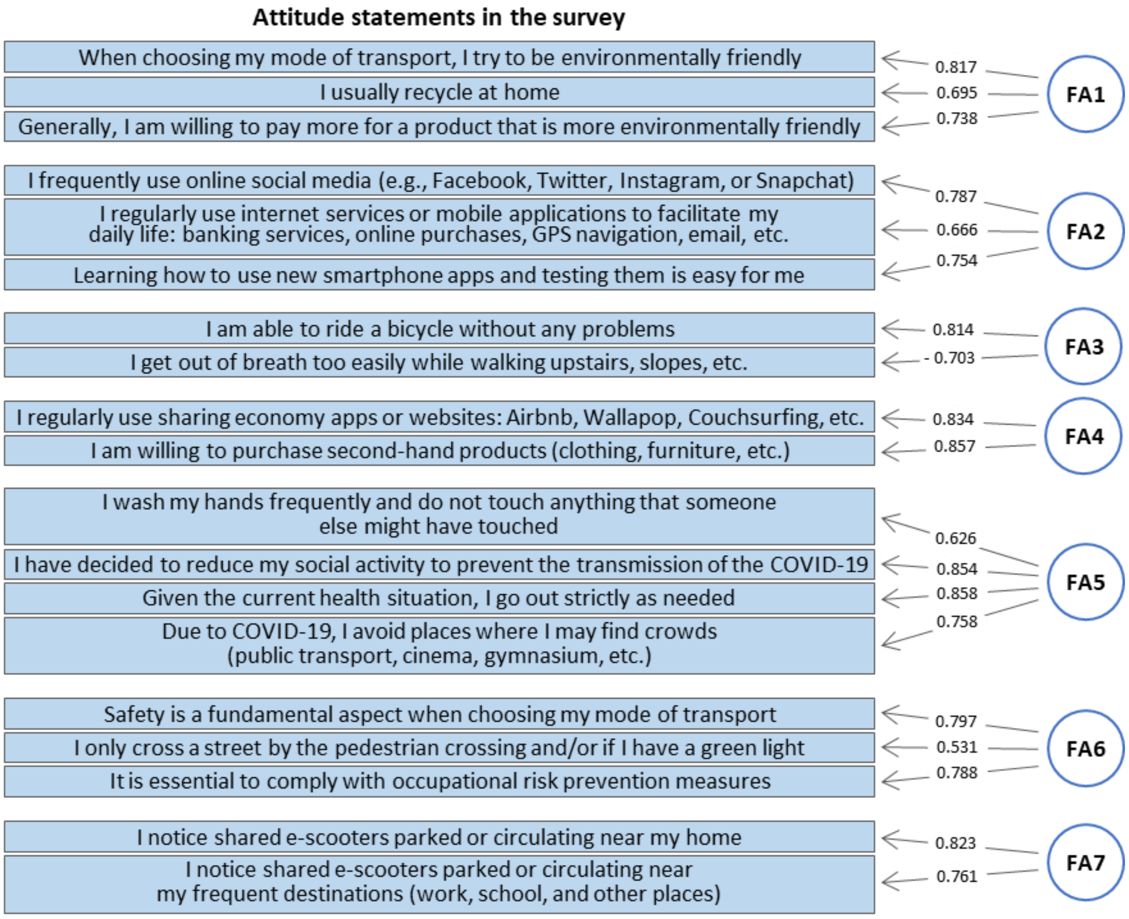

Figure 2. Latent variables constructs and factor loadings obtained in the EFA for each attitude statement in the survey questions

Two different tests were calculated to check sampling adequacy for each latent variable and the whole set, as well as certain redundancy between the variables: the Kaiser-Meyer-Olkin (KMO) test and Bartlett's test of Sphericity. First, the KMO value of 0.740 upholds the adequacy of the sample, so it was plausible to use factor analysis for the data of this study. Second, the p-value from Bartlett's test of Sphericity indicated the adequacy of conducting factor analysis techniques. Finally, multiple overall goodness-of-fit statistics were conducted in the CFA framework to determine the extent to which the postulated structure is consistent with the EFA results. These statistics also test whether the specific theoretical hypothesis fits with the latent variable measurement model. As can be observed in Table 5, the results obtained uphold the validity of the latent constructs according to the cutoff values recommended by Akaike (1987), Hu and Bentler (1999), and Kline (2016).

Table 5. Goodness-of-fit statistics conducted in the factor analysis framework

Goodness-of-fit index	Measurement model	Recommended cutoff values
KMO test (overall)	0.740	≥ 0.50
Root Mean Square Error of Approximation (RMSEA)	0.045	≤ 0.08
Comparative Fit Index (CFI)	0.923	≥ 0.90
Tucker Lewis Index (TLI)	0.900	≥ 0.80
Standardized Root Mean Square Residual (SRMR)	0.044	≤ 0.08

6. MODELING RESULTS AND DISCUSSION

This section reveals the model estimation results obtained from the GSEM-based analysis investigating e-scooter usage. First, we examine the modeling results for the structural relationships between individual sociodemographic and latent constructs (see Section 6.1). In Section 6.2 we briefly present the structural relationships between the first block of endogenous outcome variables (individuals' mobility rates during weekdays and weekends) and both the latent constructs and the individual sociodemographic variables. Section 6.3 addresses the outcomes from the submodels, explaining the main variables of interest: adoption and frequency of use of e-scooters (shared and private ones). Finally, Section 6.5 affords relevant implications from this research.

It is worth noting that non-statistically significant explanatory variables were excluded to get parsimonious model specifications. Nevertheless, some of these variables have been kept because of their intuitive insights and interpretation (see Tables 6 and 7, and Appendix B), which may also provide useful input in future specifications on shared mobility services using e.g. a larger sample size.

6.1 Model results for the latent variables

The modeling results for the structural relationships between individual sociodemographic inputs and the seven latent constructs are shown in Table 6. As can be observed in Table 6, household income is the sole variable that is statistically significant, presenting an inverted U-shaped effect. Medium-income individuals (between 30,000 and 59,999 Euro) show a higher environmental consciousness compared to respondents with lower and higher incomes. The modeling results also indicate a significantly higher tech-savviness for individuals with a higher level of income. As expected, familiarity with new technologies is lower as age increases.

Our findings regarding the physical agility construct indicate a lower capacity to climb stairs, slopes, and so on, and ride a bicycle for females and aged individuals. Some statistically-significant results are also obtained for several categories clearly related to older ages concerning occupation and household structure (e.g., retired people, families with children, etc.). By contrast, strong connections are also found between this latent construct and individuals with higher incomes.

As for the construct capturing individuals' willingness to share, the model finds higher sharing attitudes among females, while people aged 50 and over have a statistically significant lower sharing propensity. It is important to mention that our latent construct is also connected with new technologies and disruptive practices, such as the tendency to use sharing economy apps or websites (as is the case of the ones used for e-scooter sharing).

Concerning the latent construct capturing the preventive COVID-19 infection behavior of the individuals, the results clearly reflect a significantly higher susceptibility and sensitivity to COVID-19 as age increases. Our findings also indicate that employees are significantly less likely to have COVID-19 infection preventive behavior, which could be linked to engaging in indispensable social interactions (e.g., individuals working directly with the public or not having the possibility to telework). Finally, there is higher risk awareness and preventive behavior in families without children, compared to other household structures.

Table 6. SEM component results: sociodemographic determinants of latent variables

VARIABLES (*base category*)		**Environmental consciousness**	**Tech-savviness**	**Physical agility**	**Willingness to share**	**Preventive COVID-19 infection behavior**	**Safety awareness**	**Perceived availability of shared e-scooters**
Gender (*Male*)	Female	--	--	-0.401*** (0.073)	0.292*** (0.095)	--	0.203*** (0.038)	--
Age (*18-19*)	20-24	--	--	--	--	--	--	--
	25-34	--	--	--	--	--	--	-0.281* (0.150)
	35-49	--	-0.365*** (0.048)	--	--	0.186*** (0.062)	0.102** (0.049)	-0.281* (0.150)
	50 or more	--	-0.498*** (0.067)	-0.308** (0.135)	-0.653*** (0.165)	0.258*** (0.080)	0.266*** (0.067)	-0.380* (0.226)
Education (*Secondary education or lower*)	Bachelor's degree(s)	--	--	--	--	--	-0.110*** (0.042)	0.320** (0.136)
	Graduate degree(s)	--	--	--	--	--	--	0.323* (0.172)
Annual HH income (*Less than 18,000 Euro*)	18,000 to 29,999 Euro	0.057 (0.077)	--	--	--	--	--	--
	30,000 to 59,999 Euro	0.123* (0.071)	--	0.185* (0.101)	--	--	--	--
	60,000 Euro or more	--	0.178*** (0.055)	0.290** (0.113)	--	--	--	0.433*** (0.157)
	Without own income	0.055 (0.067)	--	--	--	--	--	-0.235* (0.136)
Occupation (*Student*)	Employed	--	--	-0.330*** (0.096)	--	-0.204*** (0.057)	--	--
	Part-time employee/student	--	--	--	--	--	--	-0.257* (0.131)
	Other	--	--	-0.428*** (0.122)	--	--	--	--
Household Structure (*Living alone*)	Living with non-relatives	--	--	--	--	--	--	--
	Couple without children	--	--	--	--	0.165** (0.067)	--	--
	Family with children	--	--	-0.171** (0.084)	--	--	--	-0.677*** (0.122)
Observations		694	694	694	694	694	694	694

Level of significance: *** p < 0.01, ** p < 0.05, * p < 0.1. Standard errors are in parentheses.

The strongest predictors of safety awareness are gender, age, and education. In this regard, women are more likely to have a higher perception of safety factors and risk aversion. The same was observed for older people than their younger counterparts, while the opposite is found for respondents with university studies. The last latent construct captured the subjective perception of the availability of e-scooter sharing services in Madrid streets. Interestingly, the model denotes that older respondents and families with children are significantly less likely to identify shared e-scooters circulating or parked around the city. By contrast, the opposite trend is found for people with higher levels of income and education.

6.2 Model results for the co-endogenous variables

This section summarizes the most relevant estimation results for the submodels explaining individuals' mobility patterns (both global mobility rates and walking trips), captured for the last weekday and non-weekday. To save space, the corresponding quantitative results arising from the modeling process are presented in Appendix B.

Some noticeable results are found concerning the influence of latent constructs on individual mobility patterns. For instance, it can be observed that individuals with higher pro-environmental attitudes make more walking trips on weekdays. Furthermore, we can also notice that individuals with higher sensitivity to COVID-19 are significantly less likely to have higher mobility rates, both on weekdays and non-weekdays. Finally, a statistically significant relationship is reasonably found between making more walking trips and identifying shared e-scooters circulating or parked around the city.

The findings also show a strong relationship between individuals' mobility patterns and some sociodemographic variables. According to the modeling results, young and highly educated people present higher mobility rates on non-working days, both in general mobility and walking mobility. Furthermore, middle-income groups and people who declared to use public transport frequently, show higher mobility rates on weekdays. Finally, weekday mobility is also greater among individuals residing outside inner districts, indicating the greater need to commute in these areas of the city.

6.3 Model results for e-scooter usage

This section presents the modeling results for the main variables of interest in this research: adoption and frequency of use of e-scooters (shared and private ones). We should keep in mind that these submodels jointly consider, as determinants of the variables of interest: i) latent constructs explained in Sections 5 and 6.1; ii) the sociodemographic and travel-related exogenous variables; and iii) the co-endogenous variables explained in Section 6.2 (i.e., overall mobility rates and walking trips variables).

Furthermore, to control for the potential self-selection effect coming from non-users, the submodels for frequency of use only consider adopters of these modes. As a consequence, the subsamples are reduced: the submodel of frequency of use of shared e-scooters has a subsample of 276 individuals, while for the case of frequency of use of private e-scooters, the subsample includes 110 individuals. Finally, the model also assumed that the adoption of e-scooter sharing may influence the usage of private e-scooters.

6.3.1 Adoption and frequency of use of shared e-scooters

The modeling results for the adoption and frequency of use of shared e-scooters are presented in the first and second numeric columns of Table 7, respectively. Noticeable insights are found for some latent variables influencing the use of shared e-scooters. Regarding the adoption variable, individuals with a higher propensity to purchase second-hand products and prone to use sharing economy platforms, present a significantly higher likelihood of adopting e-scooter sharing services in Madrid. Furthermore, e-scooter sharing adoption is significantly higher among those respondents who identify shared e-scooters circulating or parked around the city. This finding could be considered as a proxy of the influence of perceived reliability in the context of e-scooters obtained by Javadinasr et al. (2022) for the case of Chicago (US). At this point, we should recall that these two latent variables are related to younger segments of the population in our model.

Although no statistically significant results were found for pro-environmental behaviors in the adoption of shared e-scooters, a positive relationship with the frequency of use is observed. This finding may indicate that this transport mode is perceived as green mobility only among frequent users. Along the same line, previous research studies such as Eccarius and Lu (2020), and Mitra and Hess (2021) also found that pro-environmental behaviors play an important role in the potential use of shared e-scooters. Interestingly, opposite results were found by Aguilera-García et al. (2022) on the influence of environmental consciousness in relation to carsharing services in the cities of Madrid and Munich.

As expected, safety awareness is negatively related to the frequency of use. This means that e-scooter sharing users with higher concern about safety factors and risk aversion are more likely to be infrequent or occasional riders. Therefore, these results indicate that individuals' perceptions of safety factors and risk aversion potentially reduce the frequency of use of shared e-scooters.

As for the influence of sociodemographic variables, female respondents are less likely to adopt shared e-scooters. In fact, gender has been found in the previous research literature as one of the most important factors affecting e-scooter sharing use (see e.g., Fitt and Curl, 2019; Laa and Leth, 2020; Nikiforiadis et al., 2021; Oostendorp and Hardinghaus, 2022; Javadinasr et al., 2022; Reck et al., 2022). Middle-aged and especially older people are also less likely to adopt this emerging mobility service than younger individuals. Surprisingly, middle-aged users (aged between 35 and 49) in Madrid show a more intensive use compared to their counterparts. In comparison, Fitt and Curl (2019) indicate that individuals below the age of 34 are most likely to use e-scooters in New Zealand cities, while Javadinasr et al. (2022) and Laa and Leth (2020) found that the majority of shared e-scooter users are younger than 44 years old in Chicago (US) and young to middle-aged in Vienna (Austria), respectively. Similarly, previous research studies conducted for the case of Madrid have concluded that, in general terms, individuals' usage of app-based mobility services decreases as age increases (see e.g., Aguilera-García et al., 2020 for e-moped sharing; Gomez et al., 2021 for ridehailing; or Aguilera-García et al., 2022 for carsharing).

Table 7. Results of adoption and frequency of use of shared and private e-scooters

VARIABLES (*base category*)		**Adoption of e-scooter sharing** (base: never used)	**Frequency of use of e-scooter sharing** (ordinal)	**Adoption of private e-scooters** (base: never used)	**Frequency of use of private e-scooters** (ordinal)
LATENT VARIABLES	Environ. conscious.	--	0.294* (0.166)	0.280* (0.162)	--
	Tech-savviness	--	--	--	--
	Physical agility	--	--	--	--
	Willing. to share	0.343*** (0.083)	--	--	--
	COVID-19 behavior	--	--	--	1.112*** (0.458)
	Safety awareness	--	-0.437* (0.229)	--	--
	Perceived availability	0.268*** (0.074)	--	--	--
SOCIODEMOGRAPHIC VARIABLES					
Gender (*Male*)	Female	-0.846*** (0.211)	--	-0.412* (0.236)	-0.891** (0.522)
Age (*18-20*)	20-24	-0.783** (0.315)	--	--	--
	25-34	-1.193*** (0.353)	--	--	--
	35-49	-1.570*** (0.392)	0.821** (0.367)	--	--
	50 or more	-3.310*** (0.605)	--	--	--
Education (*Secondary education or lower*)	Bachelor's degree(s)	0.538** (0.226)	--	0.657** (0.256)	--
	Graduate degree(s)	--	--	0.657** (0.256)	--
Annual HH income (*Less than 18,000 Euro*)	18,000 to 29,999 Euro	--	--	-0.482* (0.255)	--
	30,000 to 59,999 Euro	0.682** (0.288)	--	-0.482* (0.255)	1.860*** (0.599)
	60,000 Euro or more	0.705** (0.336)	--	-0.848** (0.366)	1.854** (0.739)
	Without own income	--	--	--	--
Occupation (*Student*)	Employed	--	--	--	--
	Part-time employee/student	--	--	--	--
	Other	--	--	--	--
Household Structure (*Living alone*)	Living with non-relatives	--	0.646** (0.325)	--	--
	Couple without children	-0.757* (0.401)	--	--	--
	Family with children	-0.514* (0.290)	--	--	--
OTHER EXOGENOUS VARIABLES					
Public transport card ownership (*No*)	Multi-personal reloadable card	--	--	-1.065*** (0.341)	--
	Monthly/Annual season ticket	--	--	-0.654** (0.282)	--
E-bike ownership (No)	I have regular access to an e-bike	-2.716*** (0.257)	0.682** (0.345)	--	--
Vehicle ownership (*No*)	I have regular access to a vehicle	--	--	0.698** (0.303)	--
Residential location (*Inside the M30 Ring*)	Outside the M30 Ring	--	--	--	--
	Metropolitan area	--	-0.437* (0.252)	-0.728*** (0.280)	1.795** (0.619)
ENDOGENOUS VARIABLES					
Weekday mobility (*Zero trips*)	1 to 2 trips	--	--	--	--
	3 or more trips	0.391* (0.227)	--	--	--
Non-weekday mobility (*Zero trips*)	1 to 2 trips	0.644** (0.276)	0.742** (0.369)	--	--
	3 or more trips	1.364*** (0.298)	0.763** (0.367)	--	--
Weekday walking trips over 10 min (*Zero trips*)	1 to 2 trips	--	0.818*** (0.292)	--	--
	3 or more trips	--	1.600*** (0.351)	--	1.388*** (0.542)
Non-weekday walking trips over 10 min (*Zero trips*)	1 to 2 trips	--	--	--	--
	3 or more trips	--	--	--	--
Ever used e-scooter sharing (*No*)	Yes	n/a	n/a	0.955*** (0.226)	--
Constant		0.957** (0.417)	n/a	-1.961*** (0.452)	n/a
Thresholds	Thresholds 1	n/a	0.196 (0.413)	n/a	1.364*** (0.391)
	Thresholds 2	n/a	2.456*** (0.440)	n/a	n/a
	Thresholds 3	n/a	4.197*** (0.490)	n/a	n/a
Observations		694	276	694	110

Level of significance: *** p < 0.01, ** p < 0.05, * p < 0.1. Standard errors are in parentheses.

The results also show that people with a Bachelor's degree are more likely to adopt this emerging mobility service than individuals without university studies. This result is also consistent with Oostendorp and Hardinghaus (2022), and Javadinasr et al. (2022), which indicate that higher-educated individuals are more likely to use e-scooter sharing services. Statistically-significant results are also obtained for other sociodemographic variables. For instance, it is found that higher household income (above 30,000 Euro) is a significant predictor of adopting e-scooter sharing services in the case of Madrid, as it happens with e.g., ridehailing or carsharing (see Gomez et al., 2021; Aguilera-García et al. 2022). Regarding household structure, the modeling results may suggest that families would prefer to use transport modes other than e-scooters to meet their travel needs. As can be observed, the results evidence a decreasing tendency to adopt e-scooter sharing among childless couples and families with children, compared to other household structures. In addition, adopters living with non-relatives are significantly more prone to be frequent users of e-scooter sharing.

Furthermore, individuals residing beyond the municipal limits of Madrid are less likely to be frequent users of shared e-scooters compared to those living in inner neighborhoods. This result is also coherent with the higher supply of these services in highly dense and inner areas. Additionally, similar results were found in previous e-scooter sharing literature (see e.g., Jiao and Bai, 2020; Caspi et al., 2020; Bai and Jiao, 2020; Hawa et al., 2021; Nikiforiadis et al., 2021; Arias-Molinares et al., 2022), whose results indicate that higher population density, proximity to the city center, compact land use, higher employment zones, and better access to transit, are positively correlated with higher e-scooter sharing ridership.

Concerning travel-related variables, the model results indicate a lower likelihood of adopting e-scooter sharing among individuals who have access to an e-bike for their personal use, while the opposite effect is obtained in the frequency of use. This result suggests that individuals who need a micromobility device to fulfill their travel needs prefer riding their privately-owned e-bike to using e-scooter sharing, which still is a reasonable alternative for e-bike owners. Furthermore, frequent users of e-scooter sharing are also riders of e-bikes, highlighting the complementarity between these micromobility modes.

Interestingly, mobility patterns are critical factors affecting the usage of e-scooter sharing. As can be seen, explanatory variables capturing overall mobility rates (both for weekdays and non-weekdays) are significant positive predictors of e-scooter sharing adoption. Furthermore, those users with higher mobility rates during non-weekdays also present a higher frequency of use. This result may indirectly indicate that shared e-scooters are mainly used for out-of-home leisure purposes, as found in Section 3.4 and in accordance with McKenzie (2019), Caspi et al. (2020), and Arias-Molinares et al. (2022). Additionally, a higher frequency of use of e-scooter sharing is found for people making more walking trips during weekdays, which is also congruent with the higher environmental consciousness obtained for these people.

6.3.2 Adoption and frequency of use of private e-scooters

In addition to the abovementioned model estimation results, this section discusses the results for the submodels explaining individuals' adoption and frequency of use of private e-scooters (see the third and last numeric columns of Table 7). As a reminder, the model considers that the usage of private e-scooters may be potentially impacted by the adoption of e-scooter sharing. Indeed, 65 out of 110 users of private e-scooters reported that they had also used the shared option at some point.

With regard to the influence of latent variables, individuals with pro-environmental behaviors have a significantly higher likelihood of acquiring private e-scooters in Madrid. This is an interesting outcome since it suggests that these micromobility vehicles are perceived as a green mode of transportation among the general population. In consequence, higher environmental consciousness may lead to increasing the adoption (and use) of private e-scooters.

Furthermore, the modeling clearly reflects a significantly higher intensity of use as susceptibility and sensitivity to COVID-19 increase. This result is as expected since the COVID-19 pandemic has led to positive attitudes and preferences toward private transport modes to reduce the possibility of infections (Shamshiripour et al., 2020; de Haas et al., 2020; Christidis et al., 2022). These changes in individuals' mobility behavior may reduce trips on public transport, as also indicated by Fernández Pozo et al. (2022) in the case of Madrid during the de-escalation phases.

Remarkably, sociodemographic factors play a major role when explaining the adoption of private e-scooters. Statistically significant results are obtained for gender, education, and income. As can be observed in Table 7, males, and highly educated individuals, are more likely to use e-scooters. This is totally consistent with Laa and Leth (2020), and Oostendorp and Hardinghaus (2022), which also observed that users of private e-scooters tend to be male and highly educated individuals. Regarding household income, our results point out that people are less likely to adopt private e-scooters as income brackets increase. By contrast, the likelihood of using a private e-scooter more frequently increases among those with household incomes above 30,000 Euros.

Additionally, individuals residing outside the municipal limits of Madrid are less likely to adopt private e-scooters compared to people living in inner districts. This contrasts with the results for the frequency of use as in this case proximity to the city center is negatively correlated with higher e-scooter ridership. It may indicate that individuals living in areas with low population density and compact land use are less prone to own e-scooters, although they show more intensive use of this micromobility option, likely because shared options are scarcer in the outskirts of the city.

Concerning travel-related variables, the results indicate a lower likelihood of adopting private e-scooters among people with a public transportation pass (either monthly/annual season tickets or a multi-personal reloadable card), while the opposite effect is obtained for the variable capturing for regular access to a vehicle (car/moto). This result suggests that individuals who have private e-scooters also prefer privately-owned vehicles to public transport. Furthermore, a higher frequency of use of private e-scooters is found for people making more walking trips during weekdays, which is reasonable given the partial substitution effect that may exist between these two mobility alternatives.

Finally, private e-scooter usage has been found to be positively impacted by the adoption of e-scooter sharing, as was initially assumed. In this regard, individuals who have used e-scooter sharing at least once are more likely to acquire private e-scooters. Thus, the shared mobility option influences the usage of the private one, as has been observed in previous research on shared mobility analyzing the use of bikesharing in Madrid (see e.g., the study by Julio and Monzon, 2022).

7. CONCLUSIONS AND FURTHER RESEARCH

This research provided evidence on the factors influencing the use of both shared and privately-owned e-scooters in Madrid, using a proven methodology in the field of transport research. The maturity horizon for adopting these micromobility vehicles may lead them to play a major role in urban transport, resulting in important implications for urban livability and sustainability (Fitt and Curl, 2019; Christoforou et al., 2021; Zhang et al., 2021). This research study provides valuable implications for urban dynamics and feedback for policymakers and transport planners to make appropriate decisions and better implement suitable urban policies in the aftermath of the COVID-19 pandemic.

In light of the results, the user profile of e-scooter sharing seems to be similar to that of users of other app-based shared mobility services (e.g., moped sharing, carsharing, or ridehailing), as they tend to be males, young, wealthy, well-educated people, and those who live in inner neighborhoods. Similarly, males and highly educated individuals are more likely to use privately-owned e-scooters. By contrast, the level of income and household distance to the city center showed to negatively influence e-scooter usage.

This study also helps to understand the importance of underlying constructs on e-scooter usage. The results indicate positive relationships with the use of shared e-scooters among people with pro-environmental behaviors, prone to use sharing economy platforms, with a higher propensity to purchase second-hand products, and who identify shared e-scooters circulating or parked around the city. Conversely, greater concerns about safety factors and risk aversion are negatively related to e-scooter sharing usage. Precisely, women and aged people are more susceptible to risks and are less likely to use e-scooter sharing than their counterparts. Therefore, appropriate measures to improve the safety perception, such as designing and planning a more e-scooter-friendly infrastructure (together with e.g., bikes), or providing parking facilities for shared mobility, might not only encourage women and aged people to use e-scooters more often, but also attract new people to adopt these micromobility vehicles. In this respect, it might be expected that e-scooter usage will increase over time as long as generations of young adopters get older, and the e-scooters become more familiar to other segments of the population. Then, urban planners should be also aware of the growing trend in the adoption of these vehicles to design an effective e-scooter regulation and infrastructure.

Interestingly, since our survey was conducted in 2021 when the COVID-19 pandemic was still an issue, we were able to notice the resilience and potential of riding private e-scooters to cope with this adverse situation, as occurs with other private transport modes such as cars or motorcycles (see e.g., Shamshiripour et al., 2020; de Haas et al., 2020; Christidis et al., 2022), in contrast to public transport which has been severely affected (Fernández Pozo et al., 2022; Nikolaidou et al., 2023). In this situation, e-scooters appear to be a more sustainable and affordable alternative compared to other private modes of transportation (Arias-Molinares et al., 2022), such as cars or mopeds powered by fossil fuels, especially for urban trips.

Furthermore, our findings indicate that e-scooters are perceived as a green mode of transportation, similar to other research studies on e-scooter sharing (Eccarius and Lu,2020; Mitra and Hess, 2021), e-bike sharing (Julio and Monzon, 2022) and carsharing (Acheampong and Siiba, 2020). To have positive environmental impacts, shared e-scooters must replace trips that would otherwise be done using less sustainable transport modes. As pointed out by many research studies (see e.g., Younes et al., 2020; Christoforou et al., 2021; Arias-Molinares et al., 2022), micromobility and shared e-scooters, in particular, have significant potential to promote a shift towards low-carbon mobility and reducing car dependency. In this sense, e-scooters can potentially contribute to positive impacts on urban transportation and livability, replacing single-occupancy trips and mitigating their related negative externalities such as road congestion, urban space scarcity, or greenhouse gas emissions. However, the idea that car trips are attracted by e-scooters is hardly proven in our research. In consequence, to achieve a modal shift towards sustainability, it is necessary to implement policies at the local level that encourage the use of environmentally-friendly modes and discourage motor-based mobility, e.g. through on-street parking limitations, low emission zones, or extensive pedestrian areas.

Our results evidence some complementarity between e-scooter sharing and public transport, although the e-scooter-only option seems to be the majority. Accordingly, it is unclear whether shared e-scooters are mainly used as first/last mile mobility solutions for reaching the public transport network. The research also suggests that people who own a private e-scooter also prefer privately-owned vehicles to use public transport. In this respect, policymakers should jointly promote this kind of trip to increase the attractiveness and efficiency of public transport, by e.g., establishing single fares for the combined trips, designing physical infrastructure for the combination of different transport modes, or integrating different transport modes into one service to fulfill the mobility needs (Esztergár-Kiss et al., 2022). This in turn would help open up numerous opportunities for a more sustainable mobility system in everyday life, as long as e-scooters act as feeders of the public transport system.

Shared e-scooters seem to constitute a short-distance transport solution to replace long-distance walking trips. While this trend may benefit many users by reducing their travel times, it may also bear adverse implications for urban livability and mobility, leading to negative health and environmental effects (Reck et al., 2021). At this point, it is important to note that e-scooter sharing is mainly used when the public transport supply is noticeably low, that is, during weekends, late evenings, and night periods. Additionally, leisure was the most common trip purpose reported by respondents. All these points also reinforce the importance of further collaboration and integration between public transport and micromobility, as the first and last leg of the trip, in order to increase longer intermodal trips with public transport and e-scooters in everyday mobility. As a result, e-scooters may be used more for commuting trips and replace other private fossil-fuel vehicles, thus contributing to social welfare.

Although the present research article provides valuable insights into factors affecting e-scooter usage in urban areas, several potential areas may be considered in future research. Future research might find some diverging trends between Madrid and other case studies, thereby indicating that the performance of e-scooter systems cannot be generalized to all cities worldwide. Overall, the implications for urban dynamics will depend on a variety of context-specific factors, including the availability and convenience of e-scooters, the cost of these options relative to public transport and active modes, cultural preferences, and local policies and regulations related to transportation. Indeed, urban dynamics and transport systems are in a state of flux nowadays. Additionally, site-specific parameters range unique factors to each urban environment, including population density, infrastructure, topography, or weather conditions, which collectively may influence the usage of e-scooters. Consequently, the design of effective and successful e-scooter policies requires taking account of a large number of context and site-specific parameters that vary according to the geographical context (e.g. differences between cities in Europe and Asia or the Americas) and even from city to city, such as the characteristics of the transport network, mobility dynamics, the urban form, citizens' concerns, or the social context. Additionally, other e-scooter patterns (e.g., spatial accessibility) could be interesting to be investigated through data-driven approaches. Further explorations of e-scooter usage could also consider site-specific parameters to derive accurate insights and actionable recommendations.

While the methodology used in this research can be used by policymakers and transport planners to explore e-scooter dynamics in other regions, the challenge of transferring results and findings from one location to another adds a lot of complexity to understanding and optimizing usage patterns of e-scooters. This issue requires careful consideration due to the intricate interplay of site-specific parameters. While some principles and trends might exhibit a degree of universality (e.g., increased e-scooter usage during pleasant weather), blindly applying findings from one location to another can lead to misguided conclusions. In other words, what works well in a city with a high student population and limited parking options might not be directly applicable to a city with a predominantly elderly demographic and better public transport systems. This challenge underscores the need for localized research that acknowledges and accommodates the unique characteristics of each urban setting.

Further studies could also enrich this research with a long-term assessment of the evolution of e-scooter usage, which would provide a better overview of the spectrum of possible outcomes in different urban dynamics. In the case of Madrid, another study could be illustrative after the fleet cap on shared e-scooters is imposed. Another significant milestone for the future is to analyze in depth how to shrink the gender gap in e-scooter usage by e.g., setting suitable infrastructures and focusing on safety conditions. Finally, further contributions should address how extending pedestrian space in cities and heavier restrictions to the usage of motor-based vehicles may impact e-scooter usage.

Appendix A. Distribution of explanatory variables in the complete dataset and across e-scooter adoption

	VARIABLES	Subgroup	Complete dataset (n = 694)	Usage of shared e-scooters		Usage of private e-scooters	
				Non-user (n = 418)	User (n = 276)	Non-user (n = 584)	User (n = 110)
SOCIODEMOGRAPHICS	**Gender**	Male	59.7%	53.6%	**68.8%**	58.7%	**64.5%**
		Female	40.4%	46.4%	31.2%	41.3%	35.5%
	Age	18-19	12.7%	9.1%	**18.1%**	12.5%	13.6%
		20-24	35.7%	31.8%	**41.7%**	35.8%	35.5%
		25-34	23.9%	23.0%	25.4%	23.6%	25.5%
		35-49	18.9%	22.7%	13.0%	18.7%	20.0%
		50 or more	8.8%	13.4%	1.8%	9.4%	5.5%
	Education	Secondary education or lower	36.7%	34.0%	40.9%	38.4%	28.2%
		Bachelor's degree(s)	28.1%	24.2%	**34.1%**	26.0%	**39.1%**
		Graduate degree(s) (e.g., MS, PhD)	35.0%	41.9%	24.6%	35.4%	32.7%
		DN/DWA	0.1%	0.0%	0.4%	0.2%	0.0%
	Annual HH income	Less than 18,000 Euro	10.2%	8.6%	12.7%	9.8%	12.7%
		18,000 to 29,999 Euro	15.3%	16.5%	13.4%	16.1%	10.9%
		30,000 to 59,999 Euro	19.5%	19.6%	19.2%	19.2%	20.9%
		60,000 Euro or more	14.7%	15.6%	13.4%	15.2%	11.8%
		Without own income	22.8%	23.7%	21.4%	22.4%	24.5%
		DN/DWA	17.6%	16.0%	19.9%	17.3%	19.1%
	Occupation	Student	39.9%	35.2%	**47.1%**	39.4%	42.7%
		Employed	30.3%	36.1%	21.4%	30.7%	28.2%
		Part-time employee/student	19.2%	18.2%	20.7%	19.3%	18.2%
		Other (homemaker, unemployed, retired, etc.)	10.7%	10.5%	10.9%	10.6%	10.9%
	Household structure	Living alone	5.5%	5.5%	5.4%	5.5%	5.5%
		Living with non-relatives (e.g., roommates)	9.2%	5.5%	**14.9%**	8.6%	**12.7%**
		Couple without children	11.2%	12.9%	8.7%	12.2%	6.4%
		Family with children	73.5%	75.4%	70.7%	73.1%	75.5%
		Other types of family	0.6%	0.7%	0.4%	0.7%	0.0%
	Residential location	Madrid city: inside the M30 Ring	30.6%	25.6%	**38.0%**	30.0%	33.6%
		Madrid city: outside the M30 Ring	34.7%	36.8%	31.5%	33.4%	**41.8%**
		Metropolitan area (outside Madrid city)	28.1%	30.6%	24.3%	30.0%	18.2%
		DN/DWA	6.6%	6.9%	6.2%	6.7%	6.4%
MOBILITY-RELATED ATTRIBUTES	**Public transport card ownership**	No	21.6%	23.7%	18.5%	19.9%	**30.9%**
		Multi-personal reloadable card (10-journey and single ticket)	23.2%	26.6%	18.1%	24.7%	15.5%
		Monthly/Annual season ticket	55.2%	49.8%	**63.4%**	55.5%	53.6%
	Vehicle ownership	No	21.8%	19.4%	**25.4%**	22.9%	15.5%
		Regular access to a vehicle	78.2%	80.6%	74.6%	77.1%	**84.5%**
	E-bike ownership	No	62.4%	45.2%	**88.4%**	63.2%	58.2%
		Regular access to an e-bike	37.6%	54.8%	11.6%	36.8%	41.8%
	E-scooter ownership	No	85.3%	89.5%	79.0%	100.0%	7.3%
		Regular access to an e-scooter	14.7%	10.5%	21.0%	0.0%	**92.7%**
	Weekday mobility (excluding walking trips)	Zero trips	9.5%	10.3%	8.3%	9.8%	8.2%
		1 to 2 trips	62.8%	65.3%	59.1%	62.3%	65.5%
		3 or more trips	27.7%	24.4%	**32.6%**	27.9%	26.4%
	Non-weekday mobility (excluding walking trips)	Zero trips	17.3%	21.1%	11.6%	18.5%	10.9%
		1 to 2 trips	50.6%	53.1%	46.7%	50.5%	51.8%
		3 or more trips	32.1%	25.8%	**41.7%**	31.0%	**37.3%**
	Weekday walking trips over 10 min	Zero trips	21.5%	21.3%	21.7%	20.9%	24.5%
		1 to 2 trips	55.2%	56.5%	53.3%	56.2%	50.0%
		3 or more trips	23.3%	22.2%	25.0%	22.9%	25.5%
	Non-weekday walking trips over 10 min	Zero trips	17.9%	20.6%	13.8%	18.7%	14.5%
		1 to 2 trips	43.4%	42.8%	44.2%	43.0%	44.5%
		3 or more trips	38.8%	36.6%	**42.0%**	38.4%	40.9%

Appendix B. Results for the individual-level model on e-scooter use: main outcome variables of interest

VARIABLES (***base category***)		**Weekday mobility** (ordinal)	**Non-weekday mobility** (ordinal)	**Weekday walking trips** (ordinal)	**Non-weekday walking trips** (ordinal)	**Adoption of e-scooter sharing** (base: never used)	**Freq. of use of e-scooter sharing** (ordinal)	**Adoption of private e-scooters** (base: never used)	**Freq. of use of private e-scooters** (ordinal)
LATENT VARIABLES	Environmental consciousness	--	--	0.194* (0.116)	--	--	0.294* (0.166)	0.280* (0.162)	--
	Tech-savviness	--	--	--	0.272* (0.149)	--	--	--	--
	Physical agility	0.139* (0.083)	0.136* (0.075)	--	--	--	--	--	--
	Willingness to share	0.195*** (0.064)	--	--	--	0.343*** (0.083)	--	--	--
	COVID-19 behavior	-0.291** (0.144)	-0.268** (0.135)	--	--	--	--	--	1.112*** (0.458)
	Safety awareness	--	--	--	--	--	-0.437* (0.229)	--	--
	Perceived avail. of shared e-scooters	--	--	0.115** (0.058)	0.097* (0.053)	0.268*** (0.074)	--	--	--
SOCIODEMOGRAPHIC VARIABLES									
Gender (*Male*)	Female	--	--	0.386** (0.153)	0.339** (0.150)	-0.846*** (0.211)	--	-0.412* (0.236)	-0.891** (0.522)
Age	20-24	--	-0.482** (0.243)	-0.498*** (0.184)	--	-0.783** (0.315)	--	--	--
(*18-20*)	25-34	-0.395* (0.202)	-0.486* (0.291)	-0.498*** (0.184)	--	-1.193*** (0.353)	--	--	--
	35-49	--	-0.963*** (0.325)	-0.583** (0.248)	-0.792*** (0.236)	-1.570*** (0.392)	0.821** (0.367)	--	--
	50 or more	--	-1.020*** (0.369)	--	-0.556* (0.292)	-3.310*** (0.605)	--	--	--
Education	Bachelor's degree(s)	--	0.515*** (0.194)	--	--	0.538** (0.226)	--	0.657** (0.256)	--
(*Secondary education or lower*)	Graduate degree(s)	0.894*** (0.233)	0.747*** (0.241)	--	0.447** (0.200)	--	--	0.657** (0.256)	--
Annual HH income	18,000 to 29,999 Euro	0.540** (0.259)	--	0.438** (0.221)	--	--	--	-0.482* (0.255)	--
(*Less than 18,000 Euro*)	30,000 to 59,999 Euro	0.397* (0.228)	--	0.405* (0.208)	--	0.682** (0.288)	--	-0.482* (0.255)	1.860*** (0.599)
	60,000 Euro or more	0.397* (0.228)	--	--	--	0.705** (0.336)	--	-0.848** (0.366)	1.854** (0.739)
	Without own income	0.353 (0.220)	--	0.598*** (0.198)	--	--	--	--	--
Occupation	Employed	-0.889*** (0.241)	--	--	--	--	--	--	--
(*Student*)	Part-time employee/student	--	--	--	--	--	--	--	--
	Other	--	--	--	--	--	--	--	--
Household Structure	Living with non-relatives	--	--	--	--	--	0.646** (0.325)	--	--
(*Living alone*)	Couple without children	--	--	--	--	-0.757* (0.401)	--	--	--
	Family with children	0.421** (0.203)	--	--	-0.315* (0.176)	-0.514* (0.290)	--	--	--
OTHER EXOGENOUS VARIABLES									
Public transport card (*No*)	Multi-personal reloadable card	--	--	0.704*** (0.234)	0.505** (0.218)	--	--	-1.065*** (0.341)	--
	Monthly/Annual season ticket	0.775*** (0.190)	--	0.994*** (0.214)	0.636*** (0.201)	--	--	-0.654** (0.282)	--
E-bike ownership (*No*)	I have regular access to an e-bike	--	--	--	0.278* (0.151)	-2.716*** (0.257)	0.682** (0.345)	--	--
Vehicle ownership (*No*)	I have regular access to a vehicle	--	--	--	--	--	--	0.698** (0.303)	--
Residential location(*Madrid city: inside the M30 Ring*)	Madrid city: outside the M30 Ring	0.387** (0.190)	--	--	--	--	--	--	--
	Metropolitan area	0.499** (0.205)	--	0.401** (0.182)	--	--	-0.437* (0.252)	-0.728*** (0.280)	1.795** (0.619)
ENDOGENOUS VARIABLES									
Weekday mobility	1 to 2 trips	n/a	n/a	n/a	n/a	--	--	--	--
(*Zero trips*)	3 or more trips	n/a	n/a	n/a	n/a	0.391* (0.227)	--	--	--
Non-weekday mobility	1 to 2 trips	n/a	n/a	n/a	n/a	0.644** (0.276)	0.742** (0.369)	--	--
(*Zero trips*)	3 or more trips	n/a	n/a	n/a	n/a	1.364*** (0.298)	0.763** (0.367)	--	--
Weekday walking trips over 10	1 to 2 trips	n/a	n/a	n/a	n/a	--	0.818*** (0.292)	--	--
min (*Zero trips*)	3 or more trips	n/a	n/a	n/a	n/a	--	1.600*** (0.351)	--	1.388*** (0.542)
Non-weekday walking trips over	1 to 2 trips	n/a	n/a	n/a	n/a	--	--	--	--
10 min (*Zero trips*)	3 or more trips	n/a	n/a	n/a	n/a	--	--	--	--
Ever used e-scooter sharing (*No*)	Yes	n/a	n/a	n/a	n/a	n/a	n/a	0.955*** (0.226)	--
Constant		n/a	n/a	n/a	n/a	0.957** (0.417)	n/a	-1.961*** (0.452)	n/a
Thresholds	Thresholds 1	-1.211*** (0.304)	-1.788*** (0.225)	-0.576** (0.254)	-1.211*** (0.251)	n/a	0.196 (0.413)	n/a	1.364*** (0.391)
	Thresholds 2	2.275*** (0.315)	0.564*** (0.214)	2.045*** (0.268)	0.850*** (0.249)	n/a	2.456*** (0.440)	n/a	n/a
	Thresholds 3	5.381*** (0.414)	3.952*** (0.351)	4.564*** (0.344)	4.074*** (0.331)	n/a	4.197*** (0.490)	n/a	n/a
Observations		694	694	694	694	694	276	694	110

Level of significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Standard errors are in parentheses.

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