

Adoption and frequency of use of ride-hailing services in a European city: the case of Madrid

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Abstract

New app-based mobility services are revolutionizing urban transport. Particularly, ride-hailing has experienced a worldwide boom in the last decade since it provides a convenient, on-demand door-to-door service for urban trips. In parallel, an increasing number of studies have been conducted, mainly analyzing individuals' behavior towards this transport option, mobility patterns, as well as ride-hailing effects on urban sustainability. Nevertheless, the majority of these contributions focus on US cities, while almost no efforts have been devoted to other geographic areas, such as Europe. Cities in this continent present some particular characteristics that make them a case worth investigating, such as a higher presence of public transport modes or a great public concern on environmental issues. The aim of this paper is to explore travel behavior towards ride-hailing services in a European city. Based on the information collected from a survey campaign in the city of Madrid (Spain), we estimate a Generalized Heterogeneous Data Model approach to identify the key factors motivating ride-hailing adoption and frequency of use. The paper identifies a higher adoption of ride-hailing services among young, well-educated, wealthy individuals, who are familiar with new technologies. More interestingly, the research suggests a noticeable role played by environmental consciousness in ride-hailing frequency of use, compared to US cities. Particularly, individuals with lower environmental consciousness are more car-oriented, which is also linked to a more intense use of ride-hailing. By contrast, individuals with a higher environmental consciousness tend to reduce their use of ride-hailing, which reflects their propensity towards public transport in a transit-intensive background.

Keywords: ride-hailing, ridesourcing, urban mobility, GHDM model, Madrid, Spain

1. Introduction

Urban transport worldwide has been experiencing dramatic changes in the past few years, concurrent with the progressive development of new technologies. In particular, new app-based mobility services such as carsharing, scootersharing and ride-hailing are being increasingly adopted due to, among other reasons, a partial shift in consumer mentality from ownership to accessibility (Dervojeda et al., 2013). Within these mobility services, ride-hailing –also referred as ridesourcing in the scientific literature– has experienced a boom recently, as evidenced in the business success of transportation network companies (TNCs) such as Lyft in the US, Didi in China, or Uber all over the world. The attractiveness of these ride-hailing services can be partly explained by their provision of an inexpensive, convenient, on-demand door-to-door transport alternative in urban environments (Dias et al., 2017). The service has now become an integral element of urban transport system in many cities. For instance, in San

Francisco (US) there are more than 170,000 trips by ride-hailing on a typical weekday, representing around 15% of all intra-vehicle trips in the city (SFCTA, 2017).

In line with the increasing adoption on ride-hailing services worldwide, the scientific literature devoted to this mobility option has also grown exponentially in the last years. Previous contributions on ride-hailing have been mainly devoted to two main areas: (i) investigating the factors associated with its adoption and frequency of use, and (ii) exploring the potential impacts of ride-hailing on other travel-related dimensions, such as vehicle ownership, mode choice, traffic congestion, and road safety. Further, much of this body of research is focused on very specific countries, mostly the US (see Mohamed et al., 2019; Tirachini & del Río, 2019). By contrast, little effort has been invested in studying ride-hailing behavior in other geographic areas of the world that are also experiencing significant growth in ride-hailing use, such as Europe. In this respect, European cities typically present important mobility-related differences compared to US cities, including higher population density and higher public transport use. These differences may play an important role in the adoption and evolution of ride-hailing demand and make European cities an interesting case worth investigating.

Within the above broader context, the aim of this paper is to identify the key factors motivating the adoption and frequency of use of ride-hailing services in Madrid (Spain). The research analyzes the influence of socio-demographic characteristics, unobserved psychological preferences, and mobility-related attributes on the use of ride-hailing, and compares the results with previous contributions focused on US cities. To that end, we analyze the information collected from a survey campaign conducted in 2019 in the city of Madrid. Madrid is one of the most populated metropolitan areas in Europe, with an extensive supply and demand of public transport, and a recent increasing penetration of app-based mobility services.

The paper is organized as follows. Section 2 summarizes the current state of the scientific knowledge regarding ride-hailing services, and points out some important mobility-related differences between American and European cities that motivated the research. Section 3 briefly introduces the location context of the study and presents an overview of the modelling approach. Section 4 describes the survey we conducted and presents sample descriptive statistics. Section 5 outlines the methodology employed to explore individuals' adoption and frequency of use of ride-hailing services. Section 6 presents and discusses the modelling results, and finally Section 7 summarizes the main conclusions and identifies further research areas.

2. State of knowledge

Earlier scientific contributions on ride-hailing have pointed out both positive and negative effects of ride-hailing services on overall transport mobility. As mentioned in Yu & Peng (2019), while supporters have indicated the role of ride-hailing in, for example, encouraging car-free lifestyles (Jin et al., 2018) or improving road safety (Peck, 2017), other contributions have

criticized the negative effects on traffic congestion (Standing et al., 2019; Wenzel et al., 2019; Schaller, 2018) and reduced transit use (Gehrke et al., 2018). Along these lines, some authors, such as Hall et al. (2018), have pointed out that key policy questions on the effects of ride-hailing still remain unanswered.

In the context of demand-related issues associated with ride-hailing, as pointed out by Lavieri & Bhat (2019), there have been two main directions of investigation: research contributions at **the individual level** and research contributions at the **trip level**. At the **individual level**, research papers have arrived at some consistent conclusions on the adoption and use of ride-hailing services. For instance, there is consensus evidence that ride-hailing users tend to be younger, more educated, have higher incomes, and live in urban areas (see e.g. Rayle et al., 2016 for San Francisco; Smith, 2016 for several US cities; Alemi et al., 2018 for California; Clewlow & Mishra, 2017 for multiple US cities; Chu et al., 2018 for six major US cities, and Lavieri & Bhat, 2019 for Dallas). Familiarity with new technologies has also been found to be a consistent important lifestyle factor that influences ride-hailing adoption (see e.g. Alemi et al., 2018; Lavieri & Bhat, 2019). Research also has uniformly shown that leisure is the main purpose for ride-hailing trips (see Rayle et al., 2016 for San Francisco; Zhong et al., 2018 for Shanghai; and Tirachini & del Río, 2019 for Santiago, Chile) and that this mobility option is more intensively used in denser areas (Dias et al., 2017; Conway et al., 2018). Furthermore, there is a generalized finding that public transport is among the mobility options quite substantially affected by ride-hailing. This conclusion has been obtained for the cases of San Francisco (Rayle et al., 2016; Shaheen et al., 2016), Denver (Henao, 2017), Santiago (Tirachini & del Río, 2019), Boston (Gehrke et al., 2018), as well as Chicago, Los Angeles, New York, Seattle, or Washington D.C. (Clewlow & Mishra, 2017), among others. Additionally, there is evidence that this new mobility option leads to an increase in congestion (see e.g. Gehrke et al., 2018; Clewlow & Mishra, 2017). In contrast, some other results presented in the scientific literature are contradictory. For instance, some authors have established a negative relationship between the use of ride-hailing services and vehicle ownership (see e.g. Clewlow & Mishra, 2017, Gehrke et al., 2018). However, other research has found a non-significant relationship between these two variables (Rayle et al., 2016; Tirachini & del Río, 2019), while some contributions have even concluded that ride-hailing is associated with an increase in vehicle ownership (Schaller, 2018; Gong et al., 2017). It is worth noticing that the aforementioned individual-level models of ride-hailing have not explicitly incorporated individuals' general mobility patterns as explanatory factors, as we do in our current paper.

At the **trip level**, many contributions have employed trip data obtained from ride-hailing operators to analyze the spatial and temporal distribution of demand, as well as its relationship with socioeconomic and city built-environment factors. The conclusions from these trip-level studies are again, in general, consistent and in line with research at the individual level. Ride-hailing has been found to be more intensively used in denser areas (Yu & Peng, 2019; Li et al., 2019; Goodspeed et al., 2019) and neighborhoods with a higher presence of young, well-educated, wealthy people (Goodspeed et al., 2019). Furthermore, the analyses of geo-located

trips have generally concluded an increase in congestion (Wenzel et al., 2019; Nie, 2017; Erhardt et al., 2019) and a reduction of taxi demand (Nie, 2017) due to the presence of new ride-hailing services. Additionally, Li et al. (2019) found that ride-hailing is more frequently used for non-commuting trips, while Yu & Peng (2019) observed a higher ride-hailing demand for weekend trips. However, some other results are inconclusive. For instance, Lavieri et al. (2018) pointed out a possible substitution effect between ride-hailing and public transport use, while the analysis by Hall et al. (2018) in several US urban areas suggested a complementary effect between ride-hailing and public transport use.

One important observation from the many earlier research studies identified above is that almost all of them are based on a US city, as also indicated by Mohamed (2019) and Tirachini & del Río (2019). Particularly, to our knowledge, no study of this type has been conducted in the scientific literature to analyze ride-hailing in Europe. The majority of contributions in this continent have focused on competition and regulatory issues concerning ride-hailing operation (see, for example, Thelen, 2018; De Massi, 2018; Deighton-Smith, 2018; Geradin, 2015). There is a dearth of travel behavior research in European cities in the context of ride-hailing.

At the same time, there are distinct differences between European and US cities that may lead to different ride-hailing behaviors. First, European cities are more densely populated. According to Kumar (2016), European cities have an average density of 3,000 inhab./km², almost twice as dense as North American ones. This author points out that low densities in North American cities reflect the higher prevalence of suburban living and the predominance of car travel. These urban density variations can lead to quite distinct ride-hailing tendencies, given that previous research (see, for example, Yu & Peng, 2019 and Goodspeed et al., 2019) has found that ride-hailing demand is higher in more densely populated areas within a city. Second, European cities are better served by public transit, which functions as a backbone to help support other forms of mobility. Therefore, in Europe, a culture of shared transportation is more prevalent, while traveling by private car is the default mode of choice in many US cities. This potentially brings up a rather different landscape of competition among modes in the presence of ride-hailing in European cities relative to US cities. Third, the population in European cities generally show a high concern for environmental issues, as recently pointed out in a survey on climate change conducted by the European Investment Bank (EIB, 2018). As a result of these environmental concerns, many local governments in Europe have implemented numerous measures to reduce gridlock and greenhouse gas emissions from private autos, such as congestion charging (e.g. London, Milan), low emission zones (e.g. Munich, Paris), and parking restrictions in city centers. Such higher levels of environmental concern shown in European cities may again lead to different competition structures among modes, especially between public transport options and ride-hailing services. The three differences between US and European cities just identified above, along with the almost exclusive focus of earlier studies on a US context, point to the need to explore the adoption and use of ride-hailing services in a European city context.

3. The Madrid context and the Modeling Overview

3.1. Description of the case study

Madrid is the capital of Spain and its most populated city, with a total of 3.3 million inhabitants (Madrid City Council, 2020) and an average density of 8,832 inhab./km². Population concentration is particularly intense in the inner neighborhoods (24,326 inhab./km²). Table 1 presents a few statistics comparing US cities with Madrid. In terms of density, Madrid is only surpassed by NYC in the US, and is far above other American cities previously investigated. The next two rows of Table 1 provide indications of the public transport system use and infrastructure in Madrid and large cities in the US. The intra-city modal share of public transport and active modes in Madrid is substantially more than in US cities, as is the number of rail stations within each square kilometer area. The last row of Table 1 shows the clear difference in climate change concern between inhabitants of Spain and the US according to the national-level statistics provided by EIB (2018). In this respect, it is worth noticing that environmental conditions (e.g. PM10 concentration) does not seem to differ between Madrid and US cities.

Table 1. Comparative indicators for Madrid and several US cities^{1,2}

INDICATORS		Madrid	New York City	San Francisco	Boston	Chicago	Washington DC
Population density (inhab./km ²)		8,832	11,056	7,388	5,549	4,550	4,506
Transit Use and Availability	Modal share (intra-city trips): public transport + active modes (%)	74.6	64.1	53.0	61.0	36.5	54.3
	Rail accessibility (stations/km ²)	0.81	0.58	0.64	0.41	0.25	0.51
Climate change perception: people concerned + alarmed (%)		87.5 (Spain)	65.6 (United States)				
PM10, Annual mean (ug/m ³)		10	9	9	7	12	9

Within the context of the high density, extensive public transportation supply, and high levels of environmental concern, new shared- and micro-mobility services have started to operate in recent years in the city. Ride-hailing operations originally began in late 2014, but numerous problems with Spain's transport legislature made these services forced to provide a negligible supply until 2016. Currently, there are two main operators in Madrid: Uber and the Spanish company Cabify. As of 2020, more than 8,200 ride-hailing vehicles operate in Madrid under Uber and Cabify platforms (Ministerio de Fomento, 2020).

The description of the case study is completed with a comparison of the main socio-demographics in Madrid to US cities. As can be observed in Table 2, there is a noticeably higher proportion of the elderly population (aged above 59) in Madrid (27% of total population)

¹ Developed by authors and based on WHO (2018), EIB (2018), NYC DOT (2019), BTM (2017), CCSF (2019).

² Please note that some limitations might apply when comparing data from different sources, especially across different countries. Many of the measures summarized in this table may strongly depend on the assumptions and definitions on urban boundaries for each city, and what areas are included in each region/city. This may influence the statistics reported on e.g. rail accessibility or modal share.

compared to selected US cities (between 16 and 22%). In addition, some socio-demographic groups that generally show a more intense use of ride-hailing, such as young adults or people with high university studies, represent a higher proportion in the case of Madrid. Census statistics appear to be fairly homogeneous with respect to gender. Furthermore, we can observe that level of household income is much higher in US cities than in Madrid, although these data should be interpreted with care.

Table 2. Comparison of the main socio-demographics in Madrid to US cities

VARIABLES		% POPULATION					
		Madrid	New York City	San Francisco	Boston	Chicago	Washington DC
Gender	Male	47	48	51	48	49	47
	Female	53	52	49	52	51	53
Age	Under 20	18	23	15	20	23	21
	20 to 29	10	15	17	24	17	19
	30 to 49	31	29	34	29	30	33
	50 to 59	14	12	12	11	11	10
	Above 59	27	21	22	16	19	17
Education	Non-university	66	61	41	49	59	40
	University studies	34	39	59	51	41	60
HH Income	Median HH Income (\$k)	22 ³	69	123	79	62	92
	Under \$50k	93	39	24	35	42	29
	\$50k to \$100k	5	25	18	23	26	23
	\$100k to \$200k	1	23	27	26	22	27
	Above \$200k	1	13	31	16	10	21

Source: US Census Bureau (2021) and INE (2021)

3.2. The Modeling Framework

Our exploration of individuals' behavior towards the adoption and frequency of use of ride-hailing services involves the estimation of a choice model based on the Generalized Heterogeneous Data Model (GHDM) developed by Bhat (2015). The model is estimated at the individual level, using survey data collected in the city of Madrid. The framework for the model is discussed below. This analysis at the individual level is complemented with some insights on ride-hailing use at the trip level. To that end, we explore information also collected from survey data.

3.2.1. The Endogenous Outcome Variables

The **individual level** analysis models the ride-hailing adoption and frequency of use (see Figure 1), along with four additional outcome variables. Ride-hailing adoption is represented

³ Household income statistics for Madrid are provided in Table 2 at national currency units (Euro). When comparing with US cities, the reader should take into account that the median of household income for Madrid, once purchasing parity is controlled for, is \$35k.

as a binary variable indicating whether the individual has ever used ride-hailing services. Ride-hailing frequency is represented as an ordinal variable in five categories: (1) used, but not in the past six months, (2) used, but not in the last month, (3) used for 1-4 trips in the last month, and (4) used for 5-8 trips in the last month, and (5) used for more than 8 trips in the last month. Compared to previous studies that only consider the trips made in the last 30 days (see e.g. Lavieri & Bhat, 2019; Dias et al., 2017), we have opted to take into account a longer time-span. This approach allows us to include occasional and rare users of these services, which is important in the case of Madrid for two main reasons. First, ride-hailing is a relatively-new mobility service in the city, and so the familiarity (and consequently, frequency of use) observed for certain segments of the population may be rather low. Second, the intense use of public transport and active modes in the city, together with a wide variety of other new mobility options (car-sharing, moped and kick scooter sharing, and bike-sharing), is likely to intrinsically result in fewer frequent ride-hailing users in Madrid relative to most US cities.

Apart from ride-hailing adoption and frequency of use, the individual-level model also considers four additional co-endogenous variables: residential location, vehicle availability, and mobility rates during both weekdays and weekends. These variables have been included in the analysis to account for the possibility that residential location, vehicle availability, and mobility rates, along with ride-hailing behaviour, are determined as a choice bundle, and to accommodate for any self-selection effects in the influence of residential location and vehicle ownership on ride-hailing behaviour. Additionally, general mobility rates have been considered as co-endogenous variables in the analysis given the potential impact of daily mobility behavior on the use of ride-hailing services. In this regard, previous research has indicated that a majority of ride-hailing trips are undertaken during weekends (Yu & Peng, 2019) and for leisure (see e.g. Rayle et al., 2016; Tirachini & del Río, 2019). Therefore, it is important to consider the influence of not only individuals' weekday mobility behavior, but also weekend mobility behavior, when modeling ride-hailing.

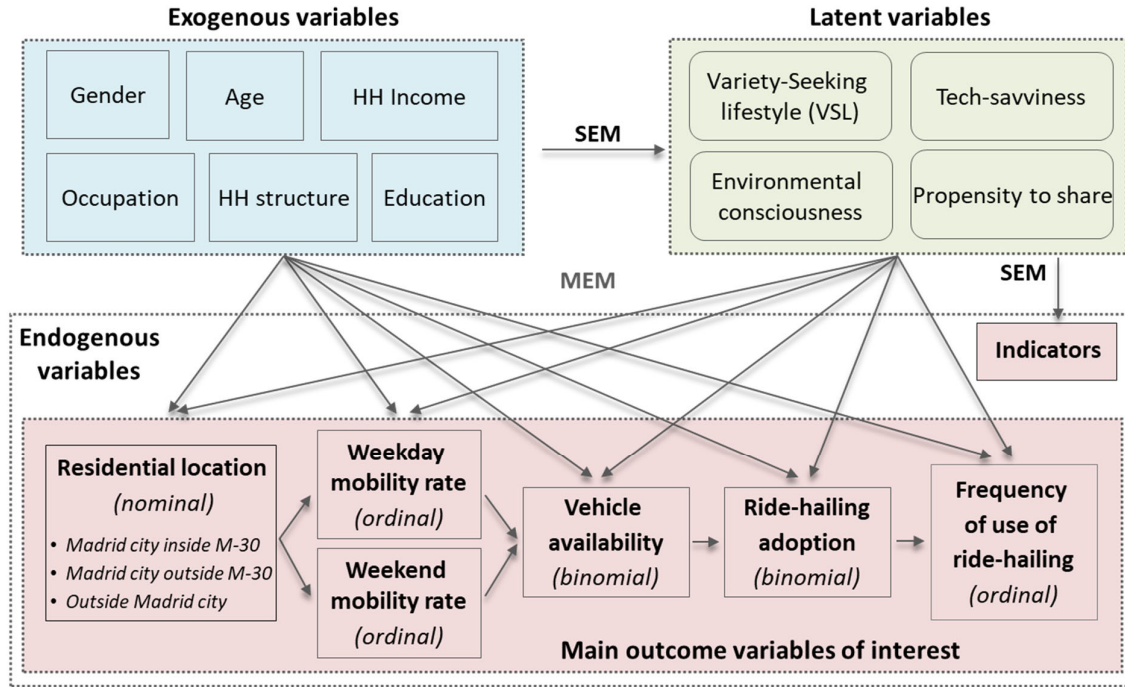
In the survey questionnaire (discussed in the next section), respondents were requested to indicate their residential location among Madrid's multiple areas, defined according to geographic centrality, transport accessibility and position with respect to the main ring roads. At the end, taking into account the low number of responses in some specific areas of Madrid city and in areas of sparse transport accessibility, residential location was primarily based on household location with respect to the main ring roads and whether the respondent lived within the confines of Madrid city or lived beyond the Madrid city boundaries in adjoining areas. Madrid city has two ring roads (an inner ring road – M30 and an outer ring road – M40), with a higher density of individuals within the first ring. Accordingly, residential location was based on a trinary nominal representation of space: (1) Lived within the inner ring road in Madrid City, (2) Lived outside the inner ring road in Madrid City, and (3) Lived outside Madrid City.

Vehicle availability was sought in the survey by asking respondents whether they frequently have access to a motorized private vehicle (car/other motorized vehicle) at home for personal use. Given the negligible presence of motorized vehicles other than cars in the household, we

created a binary variable of car availability. In the rest of this paper, we will use the terms vehicle availability and car availability interchangeably to refer to motorized car availability. In our sample, 69.1% of individuals have a vehicle available for their personal use.

The questionnaire also collected information on individuals' weekday and weekend mobility rates. Respondents reported the number of trips they made in the last weekday (Monday to Friday) and non-weekday (Saturday and Sunday), excluding trips on foot shorter than 15 min. Based on this information, an ordinal variable was created for each of the weekday and weekend mobility rates: (1) zero trips, (2) 1-2 trips, and (3) more than 2 trips. Two trips per day was established as a threshold value since it would typically indicate a pattern in which only one activity outside home was pursued on the given day.

Figure 1. Overview of the individual-level model adopted to explore ride-hailing adoption and frequency of use



The six endogenous outcome variables of interest (ride-hailing adoption, frequency, residential choice, vehicle availability, and the weekday and weekend mobility rates) were jointly modeled as a function of exogenous sociodemographic variables and a set of latent psychological constructs, the latter of which are discussed below.

3.2.2. Latent Psychological Constructs

Earlier research has clearly indicated that mobility-related characteristics (and particularly ride-hailing use) are not only determined by demographics, but also by attitudes and lifestyle preferences. Accordingly, the model includes four unobserved latent constructs that capture individuals' psychological preferences, similarly to other previous research studies in the field

of ride-hailing such as Alemi et al. (2018) or Lavieri & Bhat (2019). These are identified based on earlier studies in transportation as well as in the ethnography field that recognize these psycho-social constructs as important determinants of travel-related and technology-use patterns. The latent constructs are introduced as determinants of the six endogenous outcome variables of interest through indicator variables of the constructs collected in the survey (see next section for a modelling overview). Most of the indicators included in this research were selected from Lavieri et al. (2019) -and adapted when necessary- since they showed a good performance when studying ride-hailing adoption and frequency of use in Dallas.

The first latent construct refers to the propensity of the individual to have a variety-seeking lifestyle (VSL), that is, a tendency to purchase or try new goods or services, as well as an inclination to adopt a varied lifestyle in terms of experiences. The inclusion of this latent construct seems reasonable given that ride-hailing can still be considered a fairly new mobility option in Madrid, leading certain individuals to perceive them as a more attractive or fashionable transport option. Additionally, the individuals who follow a more variety-seeking lifestyle may tend to be more outgoing, and therefore may present higher mobility needs. This latent construct has been widely used in the field of psychology to capture differences in individuals' tendencies towards mode inertia (Rieser-Schüssler & Axhausen, 2012), and also in the use of ride-hailing (Alemi et al., 2018; Lavieri & Bhat, 2019). The indicators used to develop the VSL construct include openness to changes in general, to new experiences, to new products, and to risks, and are adapted from Schwartz et al. (2001).

The second construct refers to the tech-savviness of the individual, a latent variable widely used in the previous literature when exploring the use of new urban mobility services (see, for example, Velazquez, 2019; Astroza et al., 2017). The inclusion of this variable is clear given that ride-hailing services can be only hailed through a smartphone app. Therefore, including the familiarity of the respondent with new technologies and the use of smartphones is essential. The indicators for this construct capture adoption or daily use of new technologies, particularly: mobile apps for daily tasks, social media, and attitude towards trying new apps.

The third construct relates to the environmental consciousness of the individual, a latent variable widely adopted in the scientific literature on travel behavior (see, for example, Kamargianni et al., 2015; Davison et al., 2014; Astroza et al., 2017), and particularly ride-hailing (Lavieri & Bhat, 2019). This construct is relevant in this research due to the higher environmental concerns that European residents seem to show compared to US residents according to the EIB (2019). The latent variable is aimed at capturing pro-environmental behaviors that may, for example, lead an individual to reduce private vehicle use or show a tendency towards environmentally friendly options such as public transport, and thus potentially impact on ride-hailing use. Indicators for this construct capture preferences for environmentally friendly goods and services, perceptions of public transport, and recycling behavior at home. As for the latter, we should note that recycling practices in Spain are fully dependent on individuals' environmental consciousness since recycling services have been available in Spain for decades, but recycling is not mandatory and has no economic reward.

Finally, the fourth construct captures the propensity of the individual to share goods and services in a broad sense. Some indicators within this latent variable also refer to individuals' privacy-sensitivity. Both sharing propensity and privacy-sensitivity have been shown to influence the use of shared mobility options such as carsharing (Velazquez, 2019). Therefore, statements included such as "I prefer to buy a new product rather than buy it secondhand" is aimed at capturing individuals' willingness to use shared products/services, as it is the case of ride-hailing. This latent construct is also intended to capture individuals' propensity to avoid shared spaces with strangers, which may greatly influence them to prefer private vehicles relative to public transit (Ripplinger et al., 2012). Furthermore, given that pooled ride-hailing rides are not available for the case of Madrid, a lower sharing propensity would reflect a higher tendency to private environments, consequently potentially encouraging the use of ride-hailing rather than public transport.

As can be observed, most of the statements included in the questionnaire -as well as the attitudes measured- were presented with a "homogeneous" direction. This design might determine the way respondents answer these questions, with the potential to generate 'yes-saying', halo effects and 'politically-correctness' biases. While a more appropriate design should include higher heterogeneity in the direction of the statements, some actions have been taken to limit the potential bias in survey responses. First, many of the statements employed have been adapted from previous contributions such as Lavieri & Bhat (2019), who showed a satisfactory performance for them. Additionally, the statements concerning each latent/psychological variable are not presented in defined blocks but were mixed throughout the questionnaire (see Appendix 1) to avoid or mitigate the "yes-saying" effect.

3.2.3. The Model Structure

The modelling framework can be observed in Figure 1 and the modelling methodology adopted is based on the Generalized Heterogeneous Data Model (GHDM) developed by Bhat (2015), a methodology previously employed to analyze ride-hailing travel behavior (see e.g. Lavieri & Bhat, 2019; Vinayak et al., 2018; Lavieri et al., 2017). The GHDM represents a comprehensive approach that allows analyzing multiple variables of interest and their relationships with other transport-related variables, while controlling for observed and unobserved factors that may affect individuals' choices. Additionally, given its flexibility, the GHDM enables the joint estimation of continuous, nominal, ordinal, multiple-discrete, and count outcomes. To that end, the model establishes a parsimonious dependence structure through the stochastic latent constructs.

There are two components to the GHDM model: (1) the latent variable structural equation model (SEM), and (2) the latent variable measurement equation model (MEM). As illustrated in Figure 1, the SEM component defines each latent construct (represented as ovals in the middle panel of the figure) as a function of exogeneous socio-demographic variables (left side of the figure) and an unobserved error term (not shown in the figure). Each error term represents the effect of unobserved individual factors on a specific latent construct. Let these

unobserved factors be denoted by η_1 , η_2 , η_3 and η_4 (corresponding to one of the four latent constructs in Figure 1) and collect them in a vector $\boldsymbol{\eta}$. We assume $\boldsymbol{\eta}$ to be multivariate standard normal with a mean vector of $\mathbf{0}$ and a correlation matrix of $\boldsymbol{\Gamma}$ with six possible correlation elements (due to identification considerations, the variances of the individual $\boldsymbol{\eta}$ elements need to be normalized to 1; see Bhat, 2015). The latent constructs are stochastic because of the presence of the random elements, and, by definition, are not observed. Thus, the SEM model relationship between the socio-demographic variables and the latent constructs, as well as the correlation matrix elements of $\boldsymbol{\Gamma}$, are not directly estimable, but are estimated through observations on the latent construct indicators (see the ordinal VLS, tech-savviness, environmental consciousness, and propensity to share indicators listed under endogenous variables in the right panel of Figure 1; the actual indicators are discussed in Section 4.4) and the endogenous outcomes of interest (shown toward the right side of Figure 1). The stochastic latent constructs, along with the exogeneous socio-demographic variables, serve as determinants of the underlying latent utilities/propensities of the observed ordinal/binomial, and nominal discrete outcomes characterizing the endogenous variables of interest and the indicator variables. This is represented by the MEM relationship in Figure 1. Importantly, in addition to capturing lifestyle preference and attitude effects on ride-hailing behavior and mobility patterns, the stochastic latent constructs also serve as vehicles to allow the parsimonious joint modeling of multiple outcomes in the MEM component. Specifically, the error terms of the SEM part, which define the latent variables, permeate into the MEM part and establish a parsimonious dependence structure among all endogenous variables. For example, as found in our empirical results, if the variety-seeking construct is found to impact both the weekday and weekend mobility rates, it immediately implies an error covariance between the weekday and weekend mobility rates. Similarly, if the environmental consciousness construct impacts both vehicle availability and ride-hailing frequency, it immediately engenders a covariance structure between vehicle availability and ride-hailing frequency. A detailed description of the GHDM, as well its estimation process, is beyond the scope of this paper, but can be found in Bhat (2015).

In summary, the endogenous variables in the model include the indicators of the latent constructs and the six main outcome variables of interest referred above (listed in the right panel of Figure 1). The GHDM controls for error correlation due to the joint modeling of these variables, and accommodates recursive effects among them⁴. Multiple recursive directionalities between endogenous variables have been tested in this research. The best data fit was obtained in the causal specification considering residential location influencing mobility rates, both of them influencing vehicle availability, and these four variables finally impacting ride-hailing adoption and frequency of use. Other directions of causality could be

⁴ In joint limited-dependent variables systems in which one or more dependent variables are not observed on a continuous scale, such as the joint system considered in this paper that has ordinal, binomial, and nominal discrete dependent variables, the structural effects of one limited-dependent variable on another can only be in a single direction. See Maddala (1983) and Bhat (2015) for a more detailed explanation.

considered, concerning e.g. car ownership and mobility rates. In this respect, we may vehicle ownership (a medium-term decision) more likely to be a cause of other more short-term variables such as the daily mobility rates. However, in other cases mobility rates are not necessarily affected by vehicle ownership/availability. This seems to be the case of Madrid, a city with a dense public transportation network providing ubiquitous accessibility to the whole metropolitan area with unexpensive prices. For this city, the best data fit was obtained for the causal relationship showed in Figure 1.

3.2.4. Supplementary material: Insights on the use of ride-hailing at the trip level

The individual level model is complemented by an insight on the use of ride-hailing at the trip level. This is aimed at characterizing mobility trends by ride-hailing in the city of Madrid. To that end, we explore detailed information on the latest ride-hailing trip provided by respondents who had used ride-hailing within the past 30 days. The trip-related variables collected are: trip purpose, day-of-week, time-of-day, trip companion, and transport mode substituted for the trip (based on the response to the question “if ride-hailing were not available, which mode would you have used for the trip”).

Given that we are exploring isolated ride-hailing trips made by the individuals instead of modelling ride-hailing trips as an integral part of overall mobility patterns, these results should be interpreted with caution. This analysis it is intrinsically exploratory in nature and mainly aimed at complementing the model on ride-hailing adoption and frequency of use.

4. The Survey and Sample Description

4.1. Survey Administration

We conducted a survey aimed at capturing the main factors that might influence individuals' choices and behaviors towards the adoption and frequency of use of ride-hailing services in Madrid (Spain). The target population is the set of individuals living in and/or commuting to the city of Madrid.

Two survey waves were conducted to collect the data to obtain a heterogeneous set of respondents. The first wave was managed by GfK, a well-known transnational market research company with a huge know-how in conducting different types of surveys a surveying company, and included: (i) in-person on-street interviews in the city center and in the suburbs, and (ii) online questionnaires to panelists. In this wave, a particular effort was made to include adequate heterogeneity in terms of individual socio-demographics. The second wave was managed by the authors and included: (iii) physical on-street distribution of flyers (in the city center and in the suburbs) that explained the purpose of the research and included a link to access the online questionnaire; and (iv) dissemination of the survey link throughout social media websites and messaging apps. Both survey waves were conducted between June and October 2019, 7 days a week, avoiding the month of August, given its lower representativeness

in terms of mobility patterns. The sampling process in the first wave was co-supervised by GfK and the authors, while in the second wave it was fully supervised by the authors. Randomness of the data was checked concerning gender and age (particularly young and middle-aged adults) of the population surveyed, as well as the places and times (type of day, day of the week) to conduct and disseminate the survey. This was checked along with having a certain level of heterogeneity in income levels and use of ride-hailing services. Finally, the subsamples of each wave were analysed and compared to detect any potential bias in the data coming from e.g. survey methods.

The final design of the questionnaire sought responses on four categories of demographics, mobility patterns, and lifestyle attributes:

- *General socioeconomic and demographic information*: gender, age, household annual income, level of education, occupancy, household structure, and residential location.
- *Daily mobility trends and travel-related variables*: car availability for frequent personal use, possession of driving license, urban mobility patterns (number of trips in the last weekday and non-weekday, main trip purpose in the last weekday and non-weekday), perception of activity accessibility by public transport.
- *Adoption and use of ride-hailing services*: use of ride-hailing services ever, use of ride-hailing at least once in the last 6 months, and number of trips in the last 30 days.

Additionally, the people using ride-hailing in the last 30 days were asked to report details about their last trip, including: trip purpose, travel time, day of the week, time of day, trip companion, who made the reservation of the trip, main reasons for choosing ride-hailing, and travel mode that would have been used if ride-hailing had not been available.

- *Personal attitudes and lifestyle preferences*: individuals were requested to rate their level of agreement towards multiple statements using a five-point Likert scale. The topics included: i) propensity to adopt a variety-seeking lifestyle; ii) tech savviness; iii) environmental consciousness; and iv) propensity to use shared goods. These four sets of lifestyle preference indicators constituted the basis to develop the four latent constructs used in our study (see Section 4), which capture individuals' psychological preferences.

It should be noted that questions were not presented throughout the survey in this order. For instance, the socio-demographics section was presented at the end of the questionnaire.

A total of 1,246 valid responses were collected. The basic descriptive statistics of the demographics and mobility patterns are presented in Table 3 for some of the variables collected, and are discussed briefly in the subsequent sections. In Table 3, we also provide statistics for selected variables that were readily available from the Spain Census data for 2019 (Madrid City Council, 2020; Agencia Tributaria, 2019) to provide a comparison of the sample characteristics with the overall population characteristics of Madrid.

Table 3. Summary of the sample characteristics

			Total sample		Census data (aged 18-70)	
			Individuals	%	Population/ <i>Households</i>	%
INDIVIDUAL SOCIODEMOGRAPHICS	Gender	Male	688	55.2	1,324,589	46.0
		Female	558	44.8	1,557,425	54.0
	Age	Under 25	254	20.4	313,828	10.9
		25 to 34	383	30.7	444,968	15.4
		35 to 49	356	28.6	783,569	27.2
		50 to 59	186	14.9	479,151	16.6
		Above 59	67	5.4	859,734	29.8
		Education	Has not completed University studies	383	30.7	1,630,186
	Has completed University studies		863	69.3	857,276	34.5
	Employment	Employed	863	69.3		
		Student or part/student	277	22.2		
		Other: unemployed, retired, homemaker, etc.	106	8.5		
HOUSEHOLD CHARACTERISTICS	Household Income	Below 18,000 Euro	189	15.2	<i>682,534</i>	40.6
		18,000 to 30,000 euro	277	22.2	<i>427,844</i>	25.4
		30,000 to 60,000 Euro	314	25.2	<i>423,694</i>	25.2
		Above 60,000 Euro	141	11.3	<i>147,135</i>	8.8
		DN/DWA ⁵	325	26.1	---	0.0
	Household structure	Living alone	175	14.0		
		Living with flatmates	150	12.0		
		Couple without children	237	19.0		
		Couple with children below 24	457	36.7		
		Couple with all children above 24	118	9.5		
		Other	109	8.7		
	Residential location	Madrid city (inside M-30 ring)	587	47.1		
		Madrid city (outside M-30 ring)	473	38.0		
		Outside Madrid city (outskirts)	186	14.9		
MOBILITY-RELATED	Car availability	Yes	861	69.1		
		No	385	30.9		
	Weekday mobility	0 trips	109	8.7		
		1-2 trips	681	54.7		
		> 2 trips	456	36.6		
	Weekend mobility	0 trips	248	19.9		
		1-2 trips	583	46.8		
		> 2 trips	415	33.3		
	Ride-hailing use	Never used	458	36.8		
		Used but not in the last 6 months	111	8.9		
		Used but not in the last month	207	16.6		
Used in the last month (1-4 trips)		311	25.0			
Used in the last month (5-8 trips)		91	7.3			
Used in the last month (>8 trips)		68	5.5			
TOTAL			1,246	100.0		

⁵ DN/DWA: Do not know/do not want to answer

4.2. Individual socio-demographics and household characteristics

Table 3 shows a fairly heterogeneous distribution of individual socio-demographics and household characteristics across the sample. However, relative to the Census data, the sample presents a higher proportion of males (55.2% in the sample, compared to 46.0% from local statistics) and individuals aged under 35 (51.1% compared to 26.3%). Additionally, the sample indicates an over-representation of individuals with a high education level (69.3% of the sample has completed University studies relative to 34.5% from the Census) and high income levels (11.3% of the sample declared household income levels above 60,000 Euro, compared to 8.8% of census data). In this respect, it is worth noticing that around 25% of respondents in the sample declared not knowing their household income, or were not willing to report this information. This reluctance to report income is in line with many previous transport-related surveys collecting income data in Spain (see e.g. Heras-Molina et al., 2017; Cantos & Alvarez, 2009). In relation to household structure, there is a significant share of families with children below 24 (36.7%) and couples without children (19.0%). Employed individuals constitute a majority in the sample (69.3%).⁶

Among household characteristics, **residential location** is one of the endogenous variables of interest in our model (see Section 3.2.1). As indicated in Table 3, the majority of sample respondents live within the city of Madrid (85.1%).

4.3. Mobility-related variables

The mobility-related variables in Table 3, along with residential location, constitute the endogenous outcomes of interest in our individual-level model. Table 3 shows that 69.1% of individuals have a car frequently available for their personal use. The statistics related to weekday and weekend mobility show a generally higher out-of-home activity intensity on weekdays compared to weekends, which is not surprising because of the contribution of commute trips on weekdays. More interestingly, the table indicates that 788 respondents (63.2%) have used ride-hailing at least once, and a non-insignificant proportion of the sample

⁶The sample does differ from the Madrid population based on the exogenous sociodemographic variables of gender, age, education, and income levels, as just observed in Table 2. This fact implies that the descriptive statistics for the endogenous variables of interest in this paper from the sample cannot be generalized to the entire Madrid population. However, the focus of the current paper is not on descriptive statistics, but on estimating causal effects on the endogenous variables of interest). In such causal analyses, the issue to weight or not to weight is primarily determined by whether the sampling is dependent or independent of the dependent variables conditional on the explanatory variables. In particular, weighting is needed for consistent estimation of the causal relationship if the sampling strategy is endogenous to the modeled outcomes, but is not needed if the variation in the sampling rate is based on exogenous variables. In our case, our sampling strategy was not based on the endogenous variables, and so our sample corresponds to the case of exogenous sampling. In this situation, both the unweighted and weighted estimation will provide consistent parameter estimates of the causal relationship, but the unweighted approach is the preferred one because it is more efficient (provides more precise parameter estimates). Thus, in our model estimations, we use the unweighted approach. The reader is referred to Wooldridge (1995) and Solon et al. (2015) for an extensive discussion.

(about 13%) appear to use it at a rate of at least once a week (as obtained by adding up the last two categories of ride-hailing frequency in the table).

4.4. Latent constructs

Table 4 shows the indicators for each latent construct, as well as their sample distributions. We should remind that these attitudinal indicators were collected by using a five-point Likert scale⁷. The statistics regarding variety-seeking lifestyle suggest the highest fraction of individuals fall in the neutral category. On the other hand, respondents clearly load more heavily on being tech-savvy, which seems reasonable given the high proportion of young adults with high education levels in the sample. As expected, reported environmental consciousness is particularly high in the sample. Respondents mainly feel strongly or fully identified with environmental-oriented behaviors related to recycling (73.4%), purchase of environmentally friendly products (48.5%) and transport mode choice (57.3%). It can be observed that rates for these same environmental indicators are noticeably higher compared to the results obtained in Dallas (see Lavieri & Bhat, 2019). Also, it is reasonable that most individuals believe they have good accessibility to public transport. Finally, in terms of sharing propensity (introduced in a reversed scale in the analysis), it can be observed again that most individuals are in the middle category, with about equal proportions on either side of the middle.

Table 4. Distribution of attitudinal indicators within the sample

		Identify very little	Identify somewhat	Neutral	Identify Strongly	Identify completely
VARIETY- SEEKING LIFESTYLE	I think it is important to have all sorts of experiences and am always trying new things	4.9%	16.1%	30.9%	30.3%	17.9%
	I love to try new products before anyone else	10.3%	25.8%	31.5%	20.4%	12.0%
	Looking for adventures and taking risks is important to me	10.3%	25.4%	29.1%	25.0%	10.4%
TECH-SAVVINESS	I frequently use online social media (e.g. Facebook, Twitter, Instagram, Snapchat, etc.)	10.4%	11.1%	18.0%	25.7%	34.9%
	I regularly use internet services or mobile applications to facilitate my daily life: banking services, online purchases, GPS navigation, email, etc.	3.5%	4.8%	14.8%	27.4%	49.6%
	Learning how to use new smartphone apps and testing them is easy for me	2.8%	6.6%	19.0%	33.3%	38.3%
	I regularly use sharing economy apps or websites: Airbnb, Wallapop, Couchsurfing, etc.	17.5%	20.7%	25.5%	21.3%	15.0%
ENVIRONMENTAL CONSCIOUSNESS	When choosing my transportation mode, I try to be environmentally friendly	3.7%	12.3%	26.7%	37.4%	19.9%
	I recycle at home	5.2%	7.7%	13.6%	28.5%	44.9%
	Generally, I am willing to spend more to buy a product that is more environmentally friendly	4.4%	13.7%	33.3%	34.5%	14.0%
	My household accessibility by public transport is good	0.7%	4.6%	11.2%	21.9%	61.6%
PROPENSITY TO SHARE	I prefer to buy a new product rather than buy it second-hand	4.0%	12.4%	30.9%	30.2%	22.6%
	I am reluctant to use / put on objects that have been used by many people before me	9.8%	27.4%	30.1%	20.5%	12.3%
	I do not like travelling with strangers	11.2%	24.0%	28.4%	21.4%	14.9%

⁷ Attitudinal statements are measured through a scale from “identify very little” to “identify completely”, while the original Likert scale was of the approval/disapproval type (Likert, 1932).

5. Modelling results and discussion

This section summarizes the main results from the analysis conducted in this research. In the estimations, rather than imputing an income value for the 25% of sample that did not report income in the survey, we created a separate dummy variable category for such individuals when testing the effect of income. This has the result of using individuals with reported income values to assess appropriate income effects, while also using all individuals when estimating the effects of other model variables. We would also like to point out that a whole suite of different specifications were attempted, and the final specification was obtained based on a systematic process of testing alternative combinations of explanatory variables (and different functional forms of variables) and eliminating statistically insignificant ones while also moving toward parsimonious specifications. In the final model specification, not all the variables included are statistically significant at a 95% confidence level, but some of these were retained as they provided intuitive interpretations and insights. Important also to note is that, as indicated in Section 3.2.3, only a recursive structure of influence of the endogenous outcomes of interest is estimable among the six outcomes. In our specifications, we systematically tried all possible combinations of recursive effects among the six outcomes, and settled on the combination that provided the best data fit. In particular, a best data fit was obtained when considering mobility rates influencing car ownership decisions, compared to the opposite causal relationship. However, to be kept in mind is that the model is still a joint model that considers all the endogenous variables as a single bundled choice process, because of the error correlation generated across the endogenous outcomes through the stochastic latent constructs.

5.1. Modelling results

SEM part

The results for the individual-level model are presented in Table 5 (SEM part) and Table 6 (MEM part). From the **SEM part**, we can notice that variety-seeking lifestyle (VSL) significantly varies according to gender, age and occupation. With respect to gender, the literature on consumer behavior and human values has identified that men are more likely to exhibit variety-seeking behavior than women (McAlister & Pessemier 1982; Tscheulin, 1994) since they are more open to new experiences and changes. Further, since women experience feelings of nervousness and fear more than men in anticipation of negative outcomes, the net result may be a heightened averseness to seeking variety among women. Additionally, the relationship indicating a lower variety-seeking lifestyle as age increases would be in line with many findings in the literature on social psychology. For instance, authors such as McCrae et al. (2000), Srivastava et al. (2003) and Gonzalez-Gutierrez et al. (2015) have indicated that an individual's openness to new experiences decreases with age. Additionally, Hoyer and Ridgway (1983)

and McAlister & Pessemier 1982 noted that the desire for change decreases as people grow older due to more experience of life. The statistically significant result of a lower variety-seeking lifestyle for retired people seems to be highly related with age. Nevertheless, Srivastava et al. (2003) indicated that mixed results across studies can be found regarding the association between openness and certain socio-demographic characteristics.

Our analysis also finds a strong connection of tech savviness with income and age. These results are in line with previous research analyzing technology adoption among the Spanish population (Garrido et al., 2016; Moreira, 1998), as well as with ride-hailing demand studies in the US (Astroza et al., 2017). The relationship between technology adoption and level of income is widely referenced in the literature (see e.g. Kalba, 2008; DiMaggio & Cohen, 2005; Carey, 1989) and is typically explained by the higher financial capacity of wealthy consumers to purchase or renew technological accessories and services (e.g. cell phones). Furthermore, our results concerning a lower tech-savviness as age increases is supported by Morris & Venkatesh (2000), who indicate that young people are much more likely to be exposed to information technologies at an early age rate. More recent research (e.g. Rogers et al., 2017; Berjowsky et al., 2017) has also identified the role played by perceptions of ease of use and usefulness in the lower tech savviness of older people. Other results with respect to tech-savviness in Table 5 relate to the positive effects of education and “living with flatmates”, and the negative effects of non-student/non-employed individuals and those with grown-up children.

As for environmental consciousness, the only statistically significant variable relates to income earnings. The results suggest a kind of inverted U-shaped effect of income on environmental consciousness, with this consciousness reaching a peak in the middle income range of 30,000-60,000 euros, but decreasing at higher incomes. The lower environmental consciousness among the lowest income segment may be explained based on Maslow's theory of the hierarchy of human needs, which states that humans first focus on the survival-based instinct of meeting their basic material needs, and consider higher level needs such as the need for environmental quality only after the basic needs are satisfied. At the other end of the spectrum, there has been quite extensive research that luxury consumption is associated with the socio-cultural motivations of signaling wealth, power, and status, and privileged access to limited resources (Kastanakis and Balabanis, 2014 and Nwankwo et al., 2014), which may eclipse environmental consciousness considerations.

Finally, the results for sharing propensity, which may also be considered as a proxy of privacy-sensitivity, are reasonable. For instance, the lower sharing attitudes among women would be in line with many previous research concluding, for example, that women are more concerned about privacy and, particularly, privacy when using internet-related services (see, for example, Sheehan, 1999; Milne et al., 2004; Wills & Zeljkovic, 2011). Similarly, the SEM analysis concludes a lower sharing propensity among older segments of the population. Additionally, the model concludes a positive relationship between level of income and privacy sensitivity. Previous contributions such as Chevalier & Gutsatz (2012) indicate that this may be due to the

higher accessibility of wealthy individuals to private property, their need to feel safe and preserve their material assets, and/or their tendency towards separating or differentiating from others as a signal of exclusivity.

Table 5. Results for the individual-level model on ride-hailing use: SEM part

VARIABLES (base category)	STRUCTURAL EQUATIONS MODEL COMPONENT RESULTS							
	VSL		TECHY		ENVIRONM		SHARER	
	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat
Gender (male)								
Female	-0.153	-2.054					-0.177	-2.131
Income (below 18,000 Euro)								
18,000 to 30,000 euro			0.164	1.704	0.390	3.347		
30,000 to 60,000 Euro			0.149	1.462	0.451	3.957		
Above 60,000 Euro			0.248	1.885	0.206	1.431	-0.271	-2.271
DN/DWA			0.092	0.987	0.231	2.063		
Age (under 25)								
25 to 34	-0.189	-1.758	-0.300	-3.329				
35 to 49	-0.524	-4.762	-0.627	-6.219				
50 to 59	-0.717	-5.656	-1.067	-8.856			-0.296	2.634
Above 59	-0.717	-5.632	-1.067	-8.856			-0.296	2.634
Education (non-university)								
University studies			0.114	1.475				
Occupation (employed)								
Student or part/student								
Other: retired, unemp., etc	-0.616	-4.117	-0.471	-3.452				
Household structure (living alone)								
Living with flatmates			0.218	2.007				
Couple without children	-0.161	-1.742						
Couple with children below 24								
Couple with all children above 24			-0.187	-1.825				
Other								
Correlations between latent variables								
VSL	1.00	n/a						
TECHY	0.508	6.028	1.00	n/a				
ENVIRONM	0.425	8.303	0.356	3.921	1.00	n/a		
SHARER			-0.194	-2.884			1.00	n/a

Four out of six correlations between latent variables are statistically significant (see bottom of Table 5). Variety-seeking lifestyle, tech-savviness, and environmental consciousness are all positively correlated, while there is a negative correlation between sharing propensity and tech-savviness. Positive relationships between variety-seeking lifestyles and tech savviness have been widely referred in the literature on social psychology. For instance, Khare et al. (2010) found that innovativeness/novelty-seeking behaviors were strongly related with internet-oriented activities such as online shopping. Tech savviness has also been intrinsically related to individuals' environmental consciousness. Seçken (2005) concluded that attitudes towards technology and its utilization, and the level of computer aided education, have an influence on environmental awareness attitudes.

In terms of the correlation between environmental consciousness and VSL, variety seeking and hedonistic values have been shown to influence the purchase of eco-friendly products (Ceriak et al., 2010; Chen & Chang, 2012). Finally, many contributions in the scientific literature

have concluded a positive relationship between tech savviness and privacy concerns. For the case of Spain, Gómez-Barroso et al. (2019) have recently concluded that as users become more tech savvy, their sensitivity to privacy is also generally heightened.

The SEM estimation is made possible through the observations on the endogenous variables, which include the latent construct indicators and the four endogenous outcomes of interest (see Figure 1). The modelling results of the SEM part also include the estimates concerning the loadings of the latent constructs on the attitudinal indicators. To conserve on space, these loadings results are included in Appendix 2. As can be observed, the obtained results were all as expected.

Residential location and Mobility rates

The **MEM part** (see Table 6) analyzes the influence of both exogenous socio-demographics and latent constructs on endogenous variables. As for **residential location**, interestingly, our best specification indicated that this dimension of choice is primarily impacted by sociodemographics and not attitudinal latent constructs. As income levels increase, there is a tendency to choose to live outside of Madrid city. This result fairly reflects the spatial distribution of per capita income in the metropolitan area of Madrid (see Comunidad de Madrid, 2020), since Madrid city is bordered by seven of the 10 wealthiest towns in Spain (Pozuelo, Boadilla, Las Rozas, etc.). Age also has an effect on residential choice, with non-young individuals (over the age of 49 years) preferring to live farther away from the city center. Equivalently, young adults appear to “flock” closer to the city center, perhaps because of the higher accessibility to activities and more social vibrancy desires. A similar result is found with respect to education, with highly educated individuals preferring the city center rather than the city fringes, while the opposite appears to be the case for empty-nester type households.

Mobility rates, explicitly included as endogenous variables in the model, present some interesting findings. First, we can observe a higher propensity for **weekday and weekend mobility** among respondents with high levels of the variety-seeking lifestyle (VSL) construct. This seems reasonable given that people with a high VSL may be more open to conduct leisure activities or errands (e.g. going to the gym, meeting friends, etc.) before or after their work shift, or over the weekends. We can also notice that very few exogenous variables turn out to be statistically significant, which would indicate a certain inelasticity in individuals’ weekday and weekend mobility patterns across socio-demographics. Apart from these demographic effects, residential location very significantly influences weekday and weekend mobility rates, with mobility propensity being much higher among individuals residing in the core city center than outside, perhaps indicating the substantial activity opportunities afforded to those residing in the city center.

Table 6. Results for the individual-level model on ride-hailing use: MEM part

Variables (base category)	Residence (base: inside M30 ring)				Mobility rates weekday (ordinal)		Mobility rate weekend (ordinal)		Vehicle availability (base: no car)		Ride-hailing adoption (base: never used)		Ride-hailing frequency (ordinal)	
	Outside M30 ring		Outside Madrid city		Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat
	Coeff.	t-stat	Coeff.	t-stat										
LATENT VARIABLES														
VSL					0.253	5.395	0.109	2.158						
TECHY											0.430	4.608		
ENVIRONM									-0.265	-1.752			-0.111	-1.855
SHARER														
EXOGENOUS EFFECTS														
Gender (male)														
Female											0.088	3.869		
Income (below 18,000 Euro)														
18,000 to 30,000 euro			0.298	1.834	-0.077	-0.832			0.231	4.563				
30,000 to 60,000 Euro			0.446	2.297	-0.195	-2.022			0.618	13.339	0.214	4.894		
Above 60,000 Euro			0.557	2.459					0.481	8.129	0.487	6.797		
DN/DWA	-0.115	-2.309	0.305	1.701										
Age (under 25)														
25 to 34	-0.120	-2.725					-0.254	-2.356	0.251	5.937				
35 to 49							-0.385	-3.322	0.378	8.047	-0.115	-1.667		
Above 49	0.127	1.590	0.258	1.853	0.189	1.843	-0.446	-3.336	0.686	11.542	-0.272	-2.023		
Education (non-university)														
University studies	-0.331	-4.204	-0.437	-2.992					0.623	16.549	0.224	5.596		
Occupation (employed)														
Student or part/student	-0.154	-2.577											-0.227	-2.210
Other: reitred, unemployed, etc.			-0.608	-3.332										
Household structure (living alone)														
Living with flatmates									-0.676	-14.814	0.422	5.888		
Couple without children					-0.197	-1.936								
Couple with children below 24									0.499	13.871				
Couple with all children above 24	0.475	9.694	0.360	1.789										
Other	0.211	1.973	0.501	2.000										
Residence (inside M30 ring)														
Outside M30 ring	n/a	n/a	n/a	n/a	-0.239	-2.769	-0.145	-1.849	0.244	8.322	-0.256	-9.724	-0.367	-3.496
Outside Madrid city	n/a	n/a	n/a	n/a	-0.212	-1.904	-0.488	-3.965	0.412	9.348	-0.432	-12.122	-0.217	-1.657
Weekday mobility (zero trips)														
1 to 2 trips	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	-0.270	-5.087				
3 or more trips	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	-0.503	-9.285				
Weekend mobility (zero trips)														
1 to 2 trips	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a						
3 or more trips	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	-0.097	-3.819			0.216	2.116
Car availability (no availability)														
Availability	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	0.315	10.539	0.259	2.276
Constant	0.107	0.851	-1.036	-2.245	1.763	19.234	1.346	13.008	-0.215	-2.766	0.228	4.942	1.103	8.542
Thresholds														
Threshold2					1.798	27.363	1.326	24.483					0.856	14.021
Threshold3													1.986	22.261
Threshold4													2.538	24.430

Vehicle availability

Modelling results for **vehicle availability** indicate that, except for environmental consciousness, no other latent construct impacts vehicle availability. Environmental consciousness significantly reduces the likelihood for car availability. Given the strong connection found between pro-environmental attitudes and public transport use, this result may reflect the lower propensity to have a car for transit-oriented individuals. This result contrasts with Lavieri and Bhat (2019), who did not find a statistically significant relationship between car availability and environmental consciousness in Dallas, a car-dominated area with scarce presence of public transport. As we may expect, exogenous socio-demographic variables such as income, age, and education influence car availability, with older, wealthier, and highly educated individuals more likely than their peers to have a car available for their personal use. Respondents living with flatmates are less likely to have a car available, while the opposite is found for households with young children.

Regarding residential location, as seems reasonable, car propensity is significantly higher for residents living farther away from the city center. Additionally, there is a statistically significant negative relationship between vehicle availability and mobility rates during both weekdays and weekends. This result should be interpreted in light of the problems typically encountered when driving a private vehicle in Madrid city, particularly purely intra-city trips. In addition to recurrent congestion problems and the restrictions to the private vehicle recently implemented by the local government, on-street parking in Madrid is scarce, subject to a per-minute fee, and limited to a certain amount of time. All these factors greatly hinder the use of the private vehicle within Madrid city. This result is indeed very interesting, and quite different from what would be expected from a typical US city. Indirectly, the results also indicate the negative effect of the VSL construct on vehicle availability, as a higher VSL increases mobility rates, and mobility rates reduce vehicle availability.

Ride-hailing adoption and frequency of use

The model presents interesting findings related to ride-hailing adoption and frequency when compared with previous research on US cities. Tech-savviness is the only latent variable with a statistically significant influence on **ride-hailing adoption**. This result seems evident given that ride-hailing can be hailed only via smartphone, and so it is reasonable to expect that these services are adopted more by segments of the population with a higher familiarity with new technologies (young, well-educated, and wealthy people). The relationship between ride-hailing adoption and tech-savviness has been widely cited in the literature (see, for example, Rayle et al., 2016; Alemi et al., 2018; Lavieri & Bhat, 2019).

Apart from the indirect influence of exogenous variables through the tech-savviness latent construct, there are additional direct effects on ride-hailing adoption of exogenous socio-demographics. As can be observed from Table 6, women show a higher tendency to adopt

ride-hailing, which is also consistent with the lower tendency of this segment of the population to share goods (proxy of privacy-sensitivity). Individuals with high income, younger age, and high education are more likely to adopt ride-hailing than their corresponding peers, findings that are consistent with several other ride-hailing studies (see e.g. Chen, 2015; Rayle et al., 2016; Smith, 2016; Clewlow & Mishra, 2017; and Alemi et al., 2018, among others). Therefore, we conclude that, as in other case studies already analyzed in the US, ride-hailing users in Madrid also tend to be young, well-educated, wealthy individuals, who are familiar with new technologies.

According to the results, residential location also plays an important role in ride-hailing adoption, with individuals living outside the city center (that is, outside the first ring road) less likely to adopt ride-hailing than those residing within the first ring road. This finding is reasonable due to the higher supply of ride-hailing services in the city center and the positive association between residential density and ride-hailing adoption (Dias et al., 2017; Conway et al., 2018; Yu & Peng, 2019; Li et al., 2019; and Goodspeed et al., 2019). More interestingly, the model establishes a positive and significant relationship between car availability and ride-hailing adoption. This result contrasts with many findings usually reported for US cities (see e.g. Gehrke et al., 2018 for Boston; Alemi et al., 2019 for San Francisco), which indicate that ride-hailing is more frequently used by individuals who do not own a vehicle or who plan to replace or dispose one of their household's vehicles. It also contrasts with Ward et al. (2019), who concluded that TNC entry in the US is associated to a decline in per-capita vehicle registrations. Nevertheless, in the European context, particularly for the case of Madrid, a positive relationship between car availability and ride-hailing adoption seems reasonable. Individuals who use their private car more frequently are probably more sensitive to comfortable door-to-door trips, so that they may find a convenient alternative option in ride-hailing services when private car is less attractive (e.g. going out to eat and drink, or accessing areas with private car restrictions such as the city center). Since car availability is negatively correlated with environmental consciousness, this result may also indirectly indicate that individuals with a higher propensity towards public transport are less likely to adopt ride-hailing.

Finally, Table 6 shows relatively few exogenous variables impacting ride-hailing frequency, once ride-hailing adoption has been controlled for.⁸ The only sociodemographic variable with a statistically significant impact on ride-hailing frequency of use is occupation; specifically, students present a lower propensity to frequently use ride-hailing. The most noticeable result is that environmental consciousness reduces frequency of use of ride-hailing. This is consistent with the notion that individuals with pro-environmental attitudes likely have a higher propensity to prefer to continue using transit even in the presence of widespread ride-

⁸ We remind the reader that frequency of use was only reported by respondents who claimed to have used ride-hailing

hailing supply availability, particularly in a background with an intensive public transport supply. The result is also reasonable given that ride-hailing services are not perceived as an environmentally friendly option in Madrid. For instance, they are mostly operated by conventional (fossil fuel) vehicles. Additionally, marketing efforts conducted by ride-hailing operators have not paid much attention to environmental aspects, but rather on claiming or promoting cooperation with existing taxi services. The negative relationship between environmental consciousness and frequency of use in Madrid directly contrasts with other findings for US cities⁹. For the case of San Francisco, a metropolitan area with a high presence of public transport, Alemi et al. (2019) found a positive relationship between environmental consciousness and ride-hailing frequency of use, but did not provide an interpretation for that.

Residence location also plays a role in the frequency of use of ride-hailing, in addition to its impact on ride-hailing adoption. Individuals residing in the city center show more intensive use of ride-hailing services compared to people living in other areas. Again, this result confirms the relationship between frequency of use and population density found in the literature. According to the results corresponding to the effects of mobility rates, respondents who make more than two trips during the weekend have a statistically significantly higher propensity for ride-hailing frequently. The result emphasizes the importance of explicitly including general mobility rates as explanatory variables in models of ride-hailing frequency. Vehicle availability presents similar effects on ride-hailing frequency propensity as it does on ride-hailing adoption propensity, with higher availability leading to a higher ride-hailing use propensity. In this context, the observations of Henao (2017) are particularly relevant. Henao underscores the point that a person who normally considers the car as the main mode of transportation may be more amenable to taking ride-hailing for leisure trips (because ride-hailing is perceived as being relatively similar to private vehicle travel). But, in the case of San Francisco, Alemi et al. (2019) observed a negative relationship between ride-hailing use and own vehicle availability. In the car-dominated area of Dallas, Laverie & Bhat (2019) also observed that vehicle availability significantly reduced ride-hailing frequency.

⁹ The authors would like to clarify that the paper cannot really inform on the environmentally friendly attitudes that the population of Madrid likely has compared to the US population. The research can only inform on the values of those attitudes for the travelers in Madrid, and the degree to which individuals in the Madrid sample show environmentally friendly attitudes compared to the sample mean. Therefore, the research is not intended to compare environmental consciousness between travelers in Madrid vs. US travelers, but only indicate that the findings from this paper seem to diverge from what studies from US cities said on the relationships between this attitude and ride-hailing use.

Model Fit Comparison

The GHDM methodology used in this individual-level model considers the six endogenous variables of interest as a joint bundled choice. The improved data fit from jointly modeling these six choice dimensions may be assessed by comparing the GHDM model with an Independent Heterogeneous Data Model (IHDM) that does not consider the jointness in the six dimensions (that is, the covariances engendered by the stochastic latent constructs in the GHDM model are ignored). In this IHDM model, we introduce the exogenous variables (sociodemographic variables) used to explain the latent constructs as exogenous variables in the choice dimension equations. In this way, the contribution to the observed part of the utility due to sociodemographic variables is still maintained (and is allowed to vary relative to the GHDM to absorb, to the extent possible, the GHDM covariances due to unobserved effects). The resulting IHDM may be compared to the GHDM using the composite likelihood information criterion (CLIC) introduced by Varin and Vidoni (2005). The CLIC takes the following form (after replacing the composite marginal likelihood (CML) with the maximum approximate CML (MACML)):

$$\log L_{MACML}^*(\hat{\theta}) = \log L_{MACML}(\hat{\theta}) - tr \left[\hat{J}(\hat{\theta}) \hat{H}(\hat{\theta})^{-1} \right] \quad (1)$$

The model that provides a higher value of CLIC is preferred. The $\log L_{MACML}(\hat{\theta})$ values for the GHDM and IHDM models were estimated to be -585,985 and -593,563, respectively, with the corresponding CLIC statistic values of -588,973.57 and -594,555.84. These CLIC statistics clearly favor the GHDM over the IHDM.

The ordinal indicator variables used in the measurement equation are included solely for the purpose of model identification and do not serve any purpose in predicting the endogenous choice bundle of interest once the model is estimated. Therefore, we can also use the familiar non-nested likelihood ratio test to informally compare the two models. To do so, we evaluate a predictive log-likelihood value $L(\hat{\theta})$ of both the GHDM and IHDM models using the parameter values at the GHDM convergent values by excluding the indicator variables and focusing only on the four endogenous variables of interest. Then, one can compute the adjusted likelihood ratio index of each model with respect to the log-likelihood with only the constants as follows:

$$\bar{\rho}^2 = 1 - \frac{L(\hat{\theta}) - M}{L(c)}, \quad (2)$$

where $L(\hat{\theta})$ and $L(c)$ are the predictive log-likelihood functions at convergence and at constants, respectively, and M is the number of parameters (not including the constant(s) for each dimension and not including the ordinal indicators) estimated in the model. If the

difference in the indices is $(\bar{\rho}_2^2 - \bar{\rho}_1^2) = \tau$, then the probability that this difference could have occurred by chance is no larger than $\Phi\{-[-2\tau L(c) + (M_2 - M_1)]^{0.5}\}$ in the asymptotic limit (however, this is only an informal test, because the use of the MACML inference approach rather than the traditional maximum likelihood approach changes the asymptotic properties). A small value for the probability of chance occurrence suggests that the difference is statistically significant and that the model with the higher value for the adjusted likelihood ratio index is to be preferred. The $L(\hat{\theta})$ values (number of parameters) for the GHDM and IHDM models were computed to be -2,657.58 (number of parameters= 103) and -2,707.24 (number of parameters= 95), respectively. The $L(c)$ value was -2,989.93. The non-nested adjusted likelihood ratio test (in its informal version use here) returns a value of $\Phi(-8.67)$, which is literally zero, reinforcing the result from the more formal CLIC statistic in rejecting the IHDM model in favor of the GHDM model and underscoring the importance of considering the stochastic latent constructs that engender covariation among the choice dimensions.

5.2. Insights on the use of ride-hailing at the Trip-level

This section explores the information collected on the use of ride-hailing at the trip level in the city of Madrid. This analysis is aimed at providing some trends and insights to complement the econometric modelling conducted at the individual level. We should remind that respondents who reported having used ride-hailing services in the past 30 days were requested to provide detailed information on their last ride-hailing trip, particularly: trip purpose, day of the week, time-of-day, trip companion, and the transport mode they would have chosen in case ride-hailing had not been available for that specific trip. 466 respondents indicated that they had made at least one ride-hailing trip in the past 30 days.

Descriptive characteristics for the ride-hailing trips reported in this subsample are included in Table 77. As can be observed, leisure trips are the most common trip purpose in the sample (41.6%), which is in line with previous findings in the ride-hailing literature. The remainder of trip purposes are fairly evenly represented in the sample. In terms of day-of-week and time-of-day patterns, it is clear that the intensity of trip-making is highest on Fridays and in the late evening and night periods¹⁰. On the companionship dimension, there is about an even split between traveling alone and traveling with others.

¹⁰ It should be acknowledged that the results at the trip level can be influenced by sort of choice-based sampling. In this respect, the "most recent trip" reported in the survey strongly depends on the usage patterns of the individuals and the time of day (and the day) in which the respondents took the survey. For instance, given that no surveys were conducted or filled early in the morning, the "last trip" might underrepresent evening/late night trips for frequent users that make multiple trips by ridesourcing in the same day.

Furthermore, as seems reasonable for the case of Madrid, taxi is the main mode substituted by ride-hailing (50.6%), followed by public transport (33.3%) and, to a lesser extent, private car (9.0%). Similar results on mode substitution due to ride-hailing are obtained in other transit-intensive areas such as San Francisco, particularly regarding taxi and public transport (Alemi et al., 2018; Rayle et al., 2016). By contrast, the share of demand captured from public transport is significantly higher in Madrid than in car-dominated locations such as Dallas (see Lavieri & Bhat, 2019). Only 5.6% of the sample reported that ride-hailing substituted active modes (walking or biking). Interestingly, only 1.5% reported not being able to make the trip had ride-hailing not been available (this is in contrast to about 6% in the Dallas-Fort Worth area claiming that they could not have made the trip if not for ride-hailing). This result evidences the low “induced demand” caused by the irruption of ride-hailing services in Madrid, compared to e.g. US cities. Additionally, this supports the notion that there are alternative good transport options in Madrid, as it is the case of public transport. These services are affordable and convenient options for Madrid citizens, since they offer good accessibility to the population while charging inexpensive prices.

Table 7. Trip characteristics of the last ride-hailing trip

VARIABLE	Trips	% Sample
Trip purpose		
Intercity bus/train station or airport	70	15.0%
Work	77	16.5%
Leisure	194	41.6%
Errands & Shopping	71	15.2%
Other	54	11.6%
Day of week		
Monday-Thursday	194	41.6%
Friday	101	21.7%
Saturday-Sunday	171	36.7%
Time of day		
Morning (06-13:00h)	113	24.2%
Afternoon and early evening (13:00 – 19:00h)	91	19.5%
Late evening (19:00 – 23:30h)	120	25.8%
Night (23:30 – 6:00h)	142	30.5%
Companion		
I was alone	196	42.1%
There were family members or my couple with me	140	30.0%
There were friends with me	105	22.5%
There were co-workers with me	25	5.4%
Mode substituted		
Taxi	236	50.6%
Private vehicle	42	9.0%
Public transport: metro, bus, train, commuter rail, etc.	155	33.3%
Active modes: bike,walk	26	5.6%
Not have made the trip	7	1.5%
TOTAL	466	100.0%

Further insight can be provided from the data collected at the trip level. For instance, Table 8 provides the distribution of trip purpose data across time-related variables. In terms of the **day of the week of the last ride-hailing trip**, the more interesting finding is the strong relationship between leisure trips by ride-hailing and a more intensive use during late Fridays or weekend days. This reinforces the strong link between ride-hailing trips, leisure and weekend mobility. By contrast, the results indicate fewer work-related trips by ride-hailing during weekends, again simply a reflection of fewer work trips made over the weekend days.

Results for **time of day** are consistent with some of the observations already made, regarding (1) fewer ride-hailing trips for work during the night time period, (2) a higher level of leisure-oriented trips made by ride-hailing during the late evening/night periods and a lower level of leisure and errand trips in the morning period, and (3) fewer ride-hailing trips on Fridays during the morning period, and much higher ride-hailing trips during the late evenings/night periods over the weekends.

Table 8. Distribution of trip purpose by ride-hailing across time-related variables

VARIABLES	TRIP PURPOSE					SUM (%)
	Airport or bus / train station	Commuting or work-related	Leisure	Errands	Other	
Day of week						
Monday-Thursday	19.6	30.9	23.2	16.5	9.8	100.0
Friday	12.1	14.1	44.4	14.1	15.2	100.0
Saturday-Sunday	11.2	1.8	60.6	14.7	11.8	100.0
Time of day						
6:00 – 13:00	25.9	37.5	11.6	13.4	11.6	100.0
13:00 – 19:00	17.6	19.8	22.0	24.2	16.5	100.0
19:00 – 23:30	12.6	11.8	47.1	17.6	10.9	100.0
23:30 – 6:00	6.4	2.1	73.0	9.2	9.2	100.0

Finally, we present detailed distribution of the information concerning the **mode substituted** by ride-hailing (see Table 9). The information shows that ride-hailing has substituted for public transport primarily for leisure and errand trips. The latter may suggest difficulties (and potentially increased generalized costs) in finding parking or accessing a shopping mall via public transportation. We can also observe that the replacement of the private car is not clearly related to any trip purpose. We can also observe that public transport or active modes would be highly replaced during the weekends, suggesting a high ride-hailing demand during Saturday and Sunday that may increase traffic congestion on weekend days. Finally, the results for the “night time” period indicate that ride-hailing is less likely to take away from the private vehicle and public transport options, but more likely to take away from the taxi and active mode options during the night time period. This may be a result of perceived enhanced safety and security associated with ride-hailing relative to taxicabs and walking/bicycling alone at night.

Of course, while one can explain this result and all earlier results in more ways than one, there is a clear need to investigate these effects in much more detail in future studies within the context of overall activity-travel patterns. As indicated multiple times, this trip-level analysis is but exploratory in nature.

Table 9. Distribution of total number of trips substituted by ride-hailing across transport mode

VARIABLES	Private vehicle	Taxi	Public transport	Active modes	Not making the trip
Day of week					
Monday-Thursday	16	93	71	12	2
Friday	12	38	37	9	3
Saturday-Sunday	14	103	46	5	2
Time of day					
6:00 – 13:00	14	55	37	6	0
13:00 – 19:00	13	39	32	3	4
19:00 – 23:30	10	53	50	6	0
23:30 – 6:00	5	87	35	11	3
Trip purpose					
Airport or bus / train station	6	41	18	3	1
Commuting or work-related	8	42	24	3	0
Leisure	11	102	63	14	2
Errands	10	27	31	1	2
Other	7	22	18	5	2

5.3. Policy implications

From the results of the analysis at the individual, and the insights provided at the trip level, some policy implications may be extracted. We should point out that they are based on the results from a very specific context, particularly: a compact city with an intensive presence of public transport, having implemented restrictions to the use of private vehicles in some parts of it, and whose residents present noticeable environmental consciousness.

Ride-hailing and car-oriented alternatives

According to the individual-level model, ride-hailing is more frequently adopted and used by individuals with high private vehicle availability. Henao (2017) referred to this behavior as bi-style, according to which frequent drivers would use ride-hailing services more often for leisure trips but not necessarily for other trip purposes. In fact, the trip-level insights showed that around 60% of ride-hailing trips were captured from car-oriented alternatives (i.e., own vehicle and taxi; see Table 7). The net effect of this on traffic demand and congestion still needs additional assessment. On the one hand, ride-hailing may have positive effects in case private vehicles are kept out of streets. In particular, congestion related to finding a parking spot by private vehicles is reduced. Searching for parking is typically estimated to contribute to around 15-30% of total traffic travel in the central core area of Madrid, and so

its reduction would be greatly beneficial for road congestion and urban sustainability. In case ride-hailing use grows dramatically and captures much of the current private vehicle trips, there will also be an increase in empty vehicle trips (i.e., traveling empty to pick up a passenger), which might itself lead to severe congestion problems (see Nair et al., 2020). This fact has been observed in many cities such as San Francisco (Rayle et al., 2016), NYC (Schaller, 2017), Denver (Henao & Marshall, 2019) or Shenzhen in China (Nie, 2017), among others. On the other hand, substituting taxi by ride-hailing vehicles is relatively neutral from the point of view of urban sustainability.

Ride-hailing and Public Transport

It appears that ride-hailing fills a rather important service gap by providing opportunities to participate in leisure activities over the weekends and late nights. During the weekends and late nights, public transport supply is significantly lower in Madrid, and therefore ride-hailing would provide further mobility opportunities under low accessibility scenarios. Of course, the impact on taxicab companies and drivers remains a challenging issue, and, as in the US and other countries, fair and equitable regulation considerations need to be continually thought through in this regard. Despite this positive accessibility effect, a rather substantial share of ride-hailing demand is captured from public transport over both the weekdays and weekends, which contrasts with lower values of substitution of public transport by ride-hailing service in car-dominated contexts within the US (Lavieri & Bhat, 2019). Thus, while some public transport users (especially those who have a high environmental consciousness) may not move away from public transport, previously rare/occasional users of public transport could move even further away from these services, and potentially may no longer consider transit as an option to move around the city after the advent of a comfortable door-to-door alternative. This may also have an impact, albeit limited, on transit revenues. In any case, as long as public transport trips (and even active modes) are replaced by ride-hailing, this leads to an increase of mileage, congestion and air pollution in urban contexts. A particular issue of concern in this regard is that, according to our results, ride-hailing service will take away not only from public transportation, but also active modes of travel, particularly over the weekends. This has the twin disadvantages of increasing traffic demand as well as potentially having health-related impacts because of the reduced active mode (walking and bicycling) of travel. One strategy to reduce the uptake from public transport over the weekends may be to redesign the public transport system on weekends to supplement the reduced (from weekdays) backbone fixed transport system of operation with a limited demand-responsive pattern of service for better door-to-door weekend service. A strategy to discourage the substitution of short-distance “walkable” trips by ride-hailing may be to design a ride-hailing pricing scheme that rather steeply prices the first mile (except if the patron is mobility-challenged).

Ride-hailing and Activity Accessibility Considerations

An implication from our results is that, in Madrid, ride-hailing services appear particularly appealing to pursue errands (such as shopping and other personal business). Specifically, errand trips pursued by private vehicles or by public transport appear to get replaced by ride-hailing. The switch from private vehicles to ride-hailing may be explained by more of a hassle-free and driving-free experience, while the switch from public transport to ride-hailing may be explained by the convenience of carrying groceries. But another reason for this shift to ride-hailing for errands is because running errands typically involves chaining of multiple activities in the same sojourn from home and/or involves carrying and storing food and other perishable goods during the trip. Ride-hailing is not the most convenient for such chaining because it is more of a pure trip-based consumption service as opposed to a broader transportation option that allows a cost-effective time-based consumption service (in which the same vehicle is available to pursue multiple activities and over an extended period of time). Perhaps ride-hailing providers need to be thinking about providing a time-based option too, which effectively would combine today's ride-hailing and car-sharing services into one service. Doing so can also have a benefit of reducing congestion by having a single vehicle trace the multi-stop path desired by a single customer rather than have multiple vehicles do the same. With multiple vehicles, the empty vehicle miles of travel increase as each vehicle travels to the customer at each stop point. In this respect, Kotnou et al. (2020) shows the importance of travel demand information dissemination when it comes to matching riders to drivers that can result in savings of empty vehicle miles traveled.

Our results also point to the fact that older individuals tend to have lower tech-savviness as well as use ride-hailing services far lesser than their younger peers. At the same time, potential social exclusion due to diminished physical accessibility for elders is a relevant concern as developed countries, including Spain, face aging populations (see, for example, Walsh et al., 2016 and King, 2016). Since this older segment does not seem likely to benefit substantially from ride-hailing services as an overall accessibility enhancer with the status-quo, information campaigns and actions to increase their tech-savviness levels and acceptance of ride-hailing as a new service that may open up new socialization possibilities for them maybe beneficial.

Ride-hailing and Urban Sustainability

Overall, ride-hailing can enhance accessibility to specific segments of society and can improve safety on the roadways. But the potential consequences of ride-hailing on future urban sustainability is still of important concern and needs further analysis to choreograph a sustainable pathway forward to integrate these services within the urban mobility landscape. After all, ride-hailing adoption and frequency of use is likely to increase in coming years with the higher tech savviness levels among the population. Furthermore, climate change evolution would increase residents' environmental consciousness, leading to a wider

implementation of car restrictions in city centers and a lower use of private vehicles. Additionally, the fleet of cars will tend to become cleaner over the years. Under this future scenario, ride-hailing would become a more attractive alternative and may increase substantially in demand from its current level. For this reason, looking for coordination or integration with taxi services will be essential to avoid excessive fleets and limit the impact on congestion due to empty trips. Additionally, the evolution of ride-hailing in transit-intensive environments needs to be regulated to avoid any massive shifts from public transport alternatives; after all, public transportation ultimately represents the backbone of overall mobility in large and dense cities.

6. Conclusions and further research

This paper estimated a GHDM choice model to explore ride-hailing adoption and frequency of use in a European city, taking Madrid (Spain) as the case study. From the research, we were able to obtain some interesting conclusions.

First, as in other parts of the world, Madrid ride-hailing users also tend to be young, well-educated, wealthy individuals, who are familiar with new technologies. Additionally, the analysis revealed the importance of separating weekday and weekend patterns when modelling ride-hailing demand. This is due to the strong relationship between ride-hailing use and leisure activities, particularly in outgoing societies such as in the Mediterranean one.

Second, the research showed the key role of environmental consciousness and car propensity in transit-intensive cities. Both of them presented significant effects regarding ride-hailing use. Compared to US cities, pro-environmental attitudes in Madrid reduce the use of car-oriented options (both private vehicle and ride-hailing) in favor of environmentally-friendly modes such as public transport. Consequently, ride-hailing adoption and frequency of use were significantly higher among car prone people, for whom the comfort offered by door-to-door services is crucial, and who may adopt ride-hailing for leisure-related trips. These results are found in a context with an intensive supply of public transport and restrictions to the private vehicle in the city center, which differs from previous US case studies analyzed in the literature.

Third, the majority of ride-hailing trips in the sample substituted car-oriented options (private vehicle and taxi), although a significant share is also captured from environmentally friendly modes such as public transport and active modes. This finding makes clear that, together with the positive aspects of ride-hailing (increasing accessibility for some vulnerable segments of the population or keeping private vehicles out of streets), some negative effects can arise such as a decrease of revenues for transit operators, or an increase of empty trips made by ride-hailing vehicles as observed in many cities worldwide. Therefore, trade-offs should also be carefully evaluated. Although ride-hailing seems to be chosen currently in

very specific situations, the attractiveness of these services versus public transport should reconsider the future role of this new actor within urban mobility and sustainability.

Several future directions of research are suggested by our findings. Future contributions are needed to extend the current research to other European countries where social and mobility dynamics differ from the Mediterranean, such as in Central or Eastern Europe. Additionally, further efforts should address how perceptions towards and use of ride-hailing use may change under scenarios with heavier restrictions to the private vehicle (e.g. congestion charging policies in London or Singapore) compared to the case studies already analyzed. Finally, competition between ride-hailing and the main transport modes substituted (taxi and public transport) should be explored more deeply, given its importance in understanding the current and future role of ride-hailing in urban sustainability. In the same line, it is needed to further study transit and ridesourcing use associations before enacting pricing, technology changes, other policies implementation that could enable these modes to supplement each other and not avoid substitutions

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Appendix 1: Wording of the questionnaire conducted in Madrid (Spain)

SURVEY ON RIDE-HAILING MOBILITY BEHAVIOUR

(only for people 18+ living in Madrid)

Length of interview: 15 minutes

Interview ID:

Surveying point:

Date and time of interview:

I. INTRODUCTION

Q1 [S] Which area of the city do you live in?

- Within the M-30 ring road in Madrid City (inside “Madrid Central”)
- Within the M-30 ring road in Madrid City (outside “Madrid Central”)
- Between the M-30 and M-40 ring roads in Madrid City
- Outside the M-40 ring road in Madrid City
- Outside Madrid City

II. MAIN QUESTIONNAIRE

Q2 [S ROW] Please indicate whether you know ride-hailing.

Q3 [S ROW] Please indicate if you have ever used ride-hailing.

Q4 [S ROW] Please indicate if you have ever used ride-hailing in the last 6 months.

Q5 [Q 0-99] Please indicate how many trips you have made by ride-hailing in the last week in Madrid (consider a round trip as 2 trips).

Q6 [Q 0-99] Please indicate how many trips you have made by ride-hailing in the last 30 days (consider a round trip as 2 trips).

Mobility options	Q2. Awareness		Q3. Ever used		Q4. Ever used in the last 6 months		No. of trips made in the last...	
	1.Yes	2.No	1.Yes	2.No	1.Yes	2.No	Q5. Week	Q6. 30 days
Ridesourcing: Uber/Cabify	☐	☐	☐	☐	☐	☐	_____	_____

Personal opinions

Q7 [S ROW] Please rate how identified do you feel with the statements shown below.

[F2F ONLY] *Interviewer: Read scale.*

PROG. [RANDOMIZE]

	Very little identified (1)	Little identified (2)	Mildly identified (3)	Pretty identified (4)	Fully identified (5)
1. When choosing my transportation mode, I try to be environmentally friendly	☐	☐	☐	☐	☐
2. I recycle at home	☐	☐	☐	☐	☐
3. I regularly use sharing economy apps or websites: Airbnb, Wallapop, Couchsurfing, etc.	☐	☐	☐	☐	☐
4. I prefer to buy a new product rather than buy it second-hand	☐	☐	☐	☐	☐
5. I love to try new products before anyone else	☐	☐	☐	☐	☐
6. Looking for adventures and taking risks is important to me	☐	☐	☐	☐	☐

General mobility

Q8 [M] Do you have a valid driver's license?

1. No [S]
2. Yes (moto)
3. Yes (car)

Q9 [M] Please indicate which of the following motorized vehicles you have available at home frequently for your personal use:

1. Car
2. Moped/motorcycle
3. None

Q10 [Q 0-20] How many urban trips (within the city of Madrid) did you undertake on the ...? *(Consider a round trip itinerary as 2 trips and do not consider journeys on foot of less than 20 minutes)*

1. ... **last** working day: _____ (open answer)
2. ... **last** non-working day/weekend: _____ (open answer)

Q11.1E [S ROW] Please indicate Please rate how identified do you feel with the statement shown regarding your household accessibility:
 [F2F ONLY] *Interviewer: Read scale.*

	Very little identified (1)	Little identified (2)	Mildly identified (3)	Pretty identified (4)	Fully identified (5)
1. My household accessibility is good	☐	☐	☐	☐	☐

Personal opinions

Q12 [S ROW] Please rate how identified do you feel with the statements shown below.
 [F2F ONLY] *Interviewer: Read scale.*
 PROG. [RANDOMIZE]

	Very little identified (1)	Little identified (2)	Mildly identified (3)	Pretty identified (4)	Fully identified (5)
1. I frequently use online social media (e.g. Facebook, Twitter, Instagram, Snapchat, etc.)	☐	☐	☐	☐	☐
2. I regularly use internet services or mobile applications to facilitate my daily life: banking services, online purchases, GPS navigation, email, etc.	☐	☐	☐	☐	☐
3. I think it is important to have all sorts of experiences and I am always trying new things	☐	☐	☐	☐	☐
4. I don't mind sharing a ride with strangers if it reduces my costs	☐	☐	☐	☐	☐
5. I am reluctant to use / put on objects that have been used by many people before me	☐	☐	☐	☐	☐
6. Generally, I am willing to spend more to buy a product that is more environmentally friendly	☐	☐	☐	☐	☐

Q13 [S] Do you have a smartphone?

1. Yes
2. No

Q12 [S ROW] Please rate how identified do you feel with the statements shown below.

[F2F ONLY] *Interviewer: Read scale.*

PROG. [RANDOMIZE]

	Very little identified (1)	Little identified (2)	Mildly identified (3)	Pretty identified (4)	Fully identified (5)
1. I like driving	☐	☐	☐	☐	☐
2. It makes up for me to go in my own vehicle even if I waste time looking for parking	☐	☐	☐	☐	☐
3. Driving in traffic congestion is stressful	☐	☐	☐	☐	☐
4. I prefer to use the means of transport that allow me to take advantage of my time: reading, studying, working, using the smartphone, watching movies, etc.	☐	☐	☐	☐	☐
5. I do not like travelling with strangers	☐	☐	☐	☐	☐
6. Learning how to use new smartphone apps and testing them is easy for me	☐	☐	☐	☐	☐

III. RIDESOURCING USER BLOCK

Now we would like to gather some information about your LAST TRIP using ridesourcing.

Q17 [M] Think about the last trip you made using Uber/Cabify. What was the trip purpose?

PROG.: RANDOMIZE except OTHER

1. Going/coming back from an intercity bus / train station or airport
2. Commuting/coming back from my workplace or education center/university
3. Going/Coming back from leisure/social or recreational activity
4. Going/coming back from Shopping/Personal issues
5. Going/Coming back from Visiting relatives or friends
6. Coming back home for a different purpose
7. Attending a work meeting (outside my workplace)
9. Other (specify):

Q18 [S] Indicate the travel time of such trip (minutes)

1. Less than 5 minutes
2. Between 5 and 10 minutes
3. Between 10 and 15 minutes
4. Between 15 and 20 minutes
5. Between 20 and 30 minutes
6. More than 30 minutes

Q19 [M] Who was with you in the last trip you made using Uber/Cabify? Please mark all answers that apply.

1. I was alone
2. There were family members (all above 14 years old) or my couple with me
3. There were family members (at least one under 14 years old) with me
4. There were friends with me
5. There were co-workers with me

Q20 [S] Did you make the reservation for the trip?

1. Yes
2. No

PROG. [ONLINE: Q21 AND Q22 ON THE SAME SCREEN]

Q21 [S] Day of the week of that trip

1. Monday to Thursday
2. Friday
3. Saturday or Sunday

Q22 [S] Time of day for that trip

1. 6:00 – 9:00
2. 9:00 – 11:00
3. 11:00 – 13:00
4. 13:00 – 15:00
5. 15:00 – 17:00
6. 17:00 – 19:00
7. 19:00 – 21:00
8. 21:00 – 23:30
9. 23:30 – 2:00
10. 2:00 – 6:00

Q24 [S] If Uber/Cabify had not been available to you, which travel mode would you have used for this trip?

PROG.: RANDOMIZE except OTHER and I would not have done the trip

1. My own vehicle
2. Taxi (street hail or phone call)
3. Public transit: metro, bus, train, commuter rail, etc.
4. Bicycle
5. Walk
99. I would not have made the trip

IV. SOCIO-DEMOGRAPHIC CHARACTERISTICS

To conclude the survey, we would like to gather some information about yourself and your household.

Q46 [Q 1-99, RECODE] What is your age?

Indicate exact age: ____ ____ PROG. DO NOT ALLOW LESS THAN 18.

1. 18 - 19
2. 20 - 24
3. 25 - 29
4. 30 - 34
5. 35 - 39
6. 40 - 44
7. 45 - 49
8. 50 - 54
9. 55 - 59
10. 60 - 64
11. 65 - 69
12. 70 - 74
13. 75 - 79
14. 80 - 84
15. 85 or older

Q47 [S] You are...

[F2F ONLY] *Interviewer: check without reading.*

1. Male
2. Female

Q48 [S] What is the highest level of education you have completed?

1. No education/Primary/elementary education not completed
2. Primary education
3. First stage of high-school/compulsory education
4. Post-compulsory secondary education, with general orientation
5. Second stage of secondary education, with professional orientation (includes postsecondary education not superior)
6. Undergraduate degree (Bachelor's degree or equivalent)
7. Master's (or equivalent) degree
8. PhD (or equivalent) degree

Q49 [S] Occupation

1. Student
2. Employee
3. Part-time employee and student
4. Homemaker
5. Unemployed
6. Retired

Q50 [S] What is your household structure?

1. I live alone.
2. Sharing household (two or more people, not being a couple, who share a private dwelling)
3. Couple without children
4. Family with one or more children under 24 years

5. Family with all children above 25 years
6. Other: specify

Q52 [Q MADRID 5 DIGITS] What is your Postal Code?

— — — — —

Q53 [S] What was the gross income level of your household last year (from all sources), before taxes or other deductions?

[F2F ONLY] Interviewer: Your household includes everyone who lives in the same dwelling unit (only family, relatives and partner, not including roommates or friends). Show the ranks to the respondent to choose the option himself.

1. Under 12,000 Euro
2. From 12,001 to 18,000 Euro
3. From 18,001 to 21,000 Euro
4. From 21,001 to 30,000 Euro
5. From 30,001 to 41,000 Euro
6. From 41,001 to 60,000 Euro
7. From 60,001 to 100,000 Euro
8. Above 100,001 Euro
99. Do not know / Prefer not to answer

END OF QUESTIONNAIRE

Appendix 2: Loadings of the latent constructs on the attitudinal indicators (SEM model)

Attitudinal indicators	STRUCTURAL EQUATIONS MODEL COMPONENT RESULTS							
	VSL		TECHY		ENVIRONM		SHARER	
	Coeff.	p-value	Coeff.	p-value	Coeff.	p-value	Coeff.	p-value
<i>I think it is important to have all sorts of experiences and I am always trying new things</i>	1.226	0.000						
Constant	3.438	0.000						
<i>I love to try new products before anyone else</i>	0.994	0.000						
Constant	3.050	0.000						
<i>Looking for adventures and taking risks is important to me</i>	1	constrained						
Constant	2.994	0.000						
<i>I frequently use online social media (e.g. Facebook, Twitter, Instagram, Snapchat, etc.)</i>			1.016	0.000				
Constant			3.699	0.000				
<i>I regularly use internet services or mobile applications to facilitate my daily life: banking services, online purchases, GPS navigation, email, etc.</i>			1.100	0.000				
Constant			4.074	0.000				
<i>Learning how to use new smartphone apps and testing them is easy for me</i>			1.110	0.000				
Constant			3.934	0.000				
<i>I regularly use sharing economy apps or websites: Airbnb, Wallapop, Couchsurfing, etc.</i>			1	constrained				
Constant			3.058	0.000				
<i>When choosing my transportation mode, I try to be environmentally friendly</i>					1.141	0.000		
Constant					3.664	0.000		
<i>I recycle at home</i>					0.907	0.000		
Constant					4.064	0.000		
<i>Generally, I am willing to spend more to buy a product that is more environmentally friendly</i>					1	constrained		
Constant					3.431	0.000		
<i>My household accessibility by public transport is good</i>					1.054	0.000		
Constant					3.749	0.000		
<i>I prefer to buy a new product rather than buy it second-hand</i>							-1	constrained
Constant							-3.594	0.000
<i>I am reluctant to use / put on objects that have been used by many people before me</i>							-1.142	0.002
Constant							-2.991	0.000
<i>I do not like travelling with strangers</i>							-0.605	0.001
Constant							-3.088	0.000