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Characterizing the adoption and frequency of use of a pooled rides service

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ABSTRACT

Pooled-ride services have a significant potential for reducing traffic externalities and enhancing transportation systems in the urban environment. These services and their users' characteristics still need further inspection and exploration. We investigated factors encouraging the shift from the currently used modes to pooled-ride-services, the choice between different pooled services vehicles types, and the frequency of use of pooled-rides, using data collected via a large-scale online survey conducted in Mexico City, Mexico (CDMX) for a start-up that organizes pooled rides, Jetty. We modeled the pooled-ride-service adoption process as a function of the users' sociodemographics, latent travel attitudes, accessibility to public transportation, trip characteristics, reasons to use the service, and users' activities during the trips. We estimated hybrid choice models and binary logit models, which show that users' sociodemographic and travel attitudes are the main factors impacting the shift from different modes to pooled rides. Service-related characteristics such as multi-tasking, trip fare, and avoiding parking problems also impact the shift decision. On the other hand, the frequency of service use is mainly impacted by trip characteristics such as total trip distance, and the headway at the user's home location nearest Metro stations. Income, employment status, number of cars in the household, and gender were the only sociodemographic factors impacting the service use frequency directly and indirectly.

1. Introduction

Shared mobility services enabled by the recent mass adoption of information and communication technologies (ICT) are gaining popularity, supported by several convenience factors such as the ease of payment, fare transparency, reliability, vehicle attributes (comfort and quality), and security against crime (Tirachini and Gomez-Lobo, 2020; Rayle et al., 2016; Tirachini, 2019; Ilavarasan et al., 2018). Several shared services are covered under the umbrella of shared mobility, such as E-scooters, bikesharing carsharing, ridesharing, ride-hailing, and alternative transit system (ATS) (Shared and Digital Mobility Committee, 2018). One of the most promising services to reduce traffic congestion, and reduce traffic externalities, are pooled rides, also referred to as ridesharing and ride splitting (Hou et al., 2020; Li et al., 2019; Shaheen and Cohen, 2019).

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Tirachini et al. (2020) estimated that pooled ride could reduce the Kilometer Traveled (VKT) under specific conditions such as minimizing the empty VKT (dead mileage) (Tirachini et al., 2020). Pooled–rides services success is not always granted, where services such as UberPOOL and LyftShare failed to attract a significant number of users, despite the advantages of lower trip costs (Kang et al., 2021). The non-adoption of pooled services is supported by factors such as the expected delays, detours, and decreased travel time reliability due to the pooling nature of the service and security concerns (Moody et al., 2021; Alonso-González et al., 2020; Li et al., 2019; Lavieri and Bhat, 2019; Shaheen and Cohen, 2019). The low adoption of pooled rides is reflected in the number of the materialized pooled services. Gehrke (2018) estimated that only 20% of ride-hailing users chose pooled rides when it was available, and the materialized pooled trips, where more than one rider matched or partially matches, were estimated to be between 2%–7% of the total trips that opted for the pooling option (Henao and Marshall, 2019; Li et al., 2019). While the urban environment can increase the number of pooled rides, pooled rides' share of hailed rides is still not significant (Hou et al., 2020; Tachet et al., 2017). Rodier et al. (2016) estimated that at least 50% of the ride-hailing rides should be pooled rides to have a significant reduction in VKT. Therefore, factors impacting the demand for pooled rides are essential to be further explored and comprehended.

Current studies of pooled rides are focused on limited research areas such as the calculation of the differences in travel time and detour between the ridesourcing and pooled rides (Fielbaum and Alonso-Mora, 2020; Chau et al., 2020; Li et al., 2019), algorithm development for trip matching, and dispatching scheduling to improve ride-matching success rates (Liu and Liu, 2020; Liu et al., 2019a; Richter et al., 2019). The scarcity of user-level data has hindered the investigation of the sociodemographic factors driving many dimensions of the shared services, such as demand and use characteristics. Current studies largely depend on aggregated data sources due to the ethical and legal issues mobility companies face surrounding public sharing of consumer data (Hou et al., 2020).

We were motivated by the potential of pooled rides in enhancing traffic conditions and the ability to collect extensive user-level information. In this study, we contribute to the current literature by using two user-level extensive datasets; the first one collected service use and users information by administering a survey applied to the service users in question. In this survey, we collected detailed user and pooed trip-specific information. The second source was a service use dataset contained all the trips details performed by the survey respondents. Another source of information, such as General Transit Feed Specification files (GTFS), was used to complement the analysis. This research targeted building a deeper understanding of pooled services and extending the authors' work for demystifying the characteristics of shared (pooled) rides (Tirachini et al., 2020; Abouelela et al., 2021). We further explored pooled rides by answering the following research questions:

- (RQ1) What factors affect users' decision to adopt pooled rides?
- (RQ2) What factors influence the choice between different pooled rides services (in vans or buses)?
- (RQ3) What factors affect the frequency of use of pooled rides?
- (RQ4) What is the impact of individual travel behavior on pooled ride use frequency?

2. Literature review

2.1. Factors impacting shared mobility travel demand

Shared mobility services can be categorized into two main groups; the first group provides direct personal access to the use of vehicles for a certain period (usually to complete a trip), such as scooter-sharing, bike-sharing, and carsharing. In the case of ride-hailing, a driver is paid to perform a trip. In the second group of services, users share the ride and the subsequent costs with other people; these platforms include carpooling, vanpooling, shared ride-hailing (e.g., Uberpool and LyftShare), and alternative transit services (ATS) (Machado et al., 2018; Shaheen and Cohen, 2018; Cohen and Kietzmann, 2014; Shaheen et al., 2015). This review focuses on the second group of services, as the platform that we study caters for pooled rides.

Factors impacting shared mobility use and adoption can be categorized, but not limited to five main groups:

(i) users' sociodemographic characteristics such as gender, age, education level, ethnicity, household size, car ownership, personal income and household income (e.g. Cheng et al., 2019; Degele et al., 2018; Howe and Bock, 2018; Raux et al., 2017; Shaheen et al., 2017).

(ii) The availability of vehicles and stations nearby the beginning of a trip (Bachand-Marleau et al., 2012; Mattson and Godavarthy, 2017; Raux et al., 2017; De Lorimier and El-Geneidy, 2013).

(iii) The availability and quality of other travel options. For example, the reduced accessibility to PT increases the use of bikesharing, carsharing, ridesharing, and ride-hailing (El-Assi et al., 2017; Lin et al., 2018; Caulfield et al., 2017; Shen et al., 2018; Balac et al., 2015; Hu et al., 2018; Goodspeed et al., 2019; Atkinson-Palombo et al., 2019).

(iv) Weather, as adverse weather conditions increase the use of carsharing, ridesharing, and ride-hailing services (Goodspeed et al., 2019; Gehrke et al., 2019; Tahmasseby et al., 2016).

(v) Infrastructure, land use, and built environment (El-Assi et al., 2017; Lin et al., 2018; Sun et al., 2017; Caulfield et al., 2017). The availability of parking spaces and a higher road density influence the use of carsharing and ride-hailing services (Müller et al., 2017; Hu et al., 2018; Chen et al., 2018; Goodspeed et al., 2019). Moreover, high occupancy vehicle lanes (HOV) have been shown to be associated with the use of ridesharing services (Buliung et al., 2010; Giuliano et al., 1990). Mixed land use is found to impact carsharing and ride-hailing services (Hu et al., 2018; Alemi et al., 2018b). An increase in population density is usually found to increase the demand for shared mobility services (El-Assi et al., 2017; Sun et al., 2017; Caulfield et al., 2017; Balac et al., 2015; Hu et al., 2018; Su and Zhou, 2012; Goodspeed et al., 2019).

2.2. Shared mobility study methodology framework

2.2.1. Data collection

Different methods are applied to study factors impacting shared mobility demand and the service adoption process. These methods rely heavily on data collection to further analyze, process, and model travel behavior. Five primary data sources are commonly used in this process: surveys, open-source data, mobile phone data, GPS data, and their combinations (Chaniotakis et al., 2020). When specific individual-level information is in question, such as users' demographic, travel behavior, and motivation to use different services, online surveys, face to face interviews, and travel diaries are used (e.g. Tirachini and del Río, 2019; Arteaga-Sánchez et al., 2018; Raux et al., 2017; Schor et al., 2016; Shaheen et al., 2016a). Although surveys are helpful to investigate user-level information, they are costly and not always easy to validate (Handy, 1996; Audirac, 1999). Online surveys do not grant the representation of the general population resulting in non-coverage bias, where marginalized groups such as households with no internet access and the elderly are not accessible with such surveys. Also, some users avoid using online surveys as they fear that their private data is leaked (Gunn, 2002; Alemi et al., 2018a). The advances in information and communication technologies have positively impacted the data collection process by adding new sources of information, such as social media, that were not available to use in classical transportation studies (Liu et al., 2019b). For instance, the social network Sina Weibo was used in China to study the users' opinions regarding the TNC company DiDi (Ye et al., 2020). Also, the increased availability of GPS units and mobile phones increased the volume of the generated data, creating what is commonly named Big Data, which is increasingly being used in shared mobility studies (Noland, 2019; McKenzie, 2019).

2.2.2. Modeling techniques

The research questions that we investigate identify factors affecting the frequency of shared mobility use, the shift from different modes, and the choice between the alternative shared mobility services. These questions have a universal discrete nature that is usually modeled using econometric tools such as discrete outcome models (choice models). The type of the used model is decided by the nature of the investigated factor or commonly named dependent variable. Several studies investigate the factors impacting the adoption of shared mobility or the factors that lead to the shift from the different modes of use to shared mobility use. In such cases, binary and multinomial probit and logit models are used. For example, the adaptation of Uber and Lyft in California was investigated using a binary logit model (Alemi et al., 2018a), and a multinomial logit model was used to explore the factors that impacted the shift to ride-hailing from the different modes in Boston, USA (Gehrke et al., 2019). In other studies, the dependent variables have an ordered nature, such as ordered scale responses or ordered frequency of use, which entitle the use of models that account for the ordered nature of the investigated factors. Ordered logit and probit models are widely used for such cases. Some examples of the ordered model applications are:

(i) investigating the factors causing differences in trip duration between ride-hailing and PT. The dependent variable, time difference, was a three-level ordered categorical variable representing the time difference between the two modes (Young et al., 2020).

(ii) Generalized ordinal logit models were used to check the factors impacting the ride-hailing frequency of use. The dependent variable was the ordered levels of use frequency (Tirachini and del Río, 2019).

(iii) The factors impacting the attitudes of electrical-carsharing program members were investigated using ordered probit models; the dependent variables were an ordered five-point scale representing the different attitudes (Kim et al., 2015).

Other modeling techniques such as generalized additive mixed models, multiple regression, structural equation, and partial least squares structural equation models (PLS-SEM) were used to investigate carsharing and ridesharing use and motivation to use (Hu et al., 2018; Joo, 2017; Lempert et al., 2018; Arteaga-Sánchez et al., 2018; Ardra and Rejikumar, 2017).

3. Methods and case study

3.1. Data collection, processing, and modeling framework

Our research questions investigate the characteristics of pooled ride demand, the synergy between the existing modes of transport and pooled rides (Jetty), and the interaction between commuters' travel behavior, sociodemographics, and Jetty's actual use. Therefore, we collect and then used three sources of information.

The first data source is a survey that was deployed online to Jetty users, and it consisted of three sections:

- The first part explored the characteristics of the users' last Jetty trip, trip purpose, the modes Jetty replaces, and the modes used to access and egress Jetty and their subsequent timing.
- The second part explored Jetty users' travel behavior, activities during Jetty trips, and reasons to use the service.
- The last part investigated the sociodemographics of Jetty users, in addition to their home and work locations (zip codes)

The survey was implemented on an open-source software package limesurvey,[1] without any intervention or access by Jetty staff, in order to guarantee the transparency and the independence of the research process. The survey was deployed to Jetty users by

[1] limesurvey.com.

email. An incentive for free rides was offered to some users who completed the survey to increase the response rate. The survey was deployed between May and June 2019

The second source of information was the users' trip data retrieved from Jetty for all the survey participants for the seven months before the survey deployment. The database included trip ID, route ID, pick-up and drop-off coordinates, trip distance, number of booked tickets, fare charged, used vehicle type, and departure and arrival times. The main objective for using this information was to study the individual behavior of Jetty users.

Finally, GTFS[2] to study the spatial relationship between the existing PT modes and Jetty use. GTFS files contain information regarding the different modes station locations, time tables, and routes (Chaves-Fraga et al., 2020)

We checked the quality of the received data for the three sources of information. The survey responses were checked; uncompleted answers or duplicated entries were removed. The Jetty use database and GTFS files were checked, with no problems detected except that some variables (headways) in the GTFS files had no variability (zero variance); these variables were excluded from the modeling process. After cleaning and exploring the available databases, the next step was to prepare the data for the modeling process. Multicollinearity was checked for the different variables used in the modeling building process, using Pearson's (Spearman, 1904) correlation coefficient for the numeric variables, and Polychoric correlation coefficient (Olsson, 1979) for ordinal data. Highly correlated variables were removed from the modeling process. The distance from the user's home location to the nearest Trolley bus station is highly correlated (correlation coefficient is ≥ 0.6) with the distances to the nearest BRT, buses, Metro, and Metrobus. Only distances to the nearest Metro station and trolleybus station were kept in the model. Also, we opted to use the distances to the nearest Metro station and trolleybus station after considering the correlation as they cover more geographical area than other modes.

This research investigated the impact of the user's general travel pattern and users' travel attitude on the choice and frequency of use of shared mobility services. Attitudes are cognitive characteristics of the user that are gained over a long time, and they are reflected, under the scope of this research, on people's travel choices (Ben-Akiva et al., 2002). Explanatory Factor Analysis (EFA) was applied to the travel behavior (frequency of use) questions to understand the latent construct of the data or the travel attitude of Jetty users. EFA calculation was done in an iterative technique, where variables with factor absolute loading value less than (0.4) were removed until the EFA estimation results were stable (Hair et al., 1998).

The integration of people's attitudes on the different choice options was done by integrating the latent variable model into the choice models using Hybrid Choice Models (HCM). The expected additional knowledge and improvement in the models gained from using HCM are not always reached; in some cases, the reduced choice model performs better than the HCM in terms of the model's fit (Vij and Walker, 2016; Alemi et al., 2018a). The previous point was addressed during the estimation process, as explained in the following sections.

3.2. Case study

Mexico City (CDMX) is the capital city of Mexico, and it is located in the Valley of Mexico (ZMVM), which is the most populated area in North and Central America (United Nations Department of Economic and Social Affairs, 2016; Mejía-Dorantes and Soto Villagrán; INEGI, 2015). CDMX dwellers mainly depend on PT for their daily commute, where around 50% of the daily trips are done in PT. PT commuters in CDMX face several difficulties, such as personal security and safety, overcrowding, and sexual harassment, to the point that the metro system (subway) in CDMX is considered one of the unsafest metro systems worldwide (Rivadeneyra et al., 2015; Mejía-Dorantes and Soto Villagrán; Sheinbaum, 2018). Several shared mobility services are available in CDMX, such as ride-hailing, bikesharing, and scooter sharing (Eisenmeier, 2019; Uber, 2019).

Jetty is a digital platform that organizes pooled rides through a mobile application in CDMX. The company does not own any vehicles, but it matches users with the most suitable trip based on predefined, fixed routes and time schedules. Jetty makes deals with vehicle operators (primarily buses and vans) who are the ones that effectively run the services designed by Jetty, and Jetty collects a margin fee from the trip cost. The service routes run mainly from the north of the city, where the PT coverage is limited, to the job centers near the downtown area in Santa Fe and Polanco. The service is provided in different vehicle sizes that range from passenger cars (3-seats) to 45-seat buses. The company locates the pick-up and drop-off locations based on users' requests and actual travel demand to minimize the access and egress time (Onésimo Flores Dewey, 2019). Jetty routes service geographic areas with two distinctive attributes; (i) The north of CDMX has low accessibility to formal jobs.[3] (ii) The car ownership rate in the north of CDMX is high compared to the average city rates (Guerra, 2015).

The service has a distinctive operation scheme compared to ride pooling services as Jetty's scheme eliminates the delays resulting from the expected dynamic detouring to pick up other passengers, and it also grants the probability of being matched with other passengers. Although the Jetty operational scheme is relatively new compared to traditional shared mobility schemes, similar services are gaining popularity worldwide. Some examples for similar services are (i) Swevl,[4] which started in 35 Cairo, Egypt and managed to expand its operations to 6 countries already, with 1.8 million users, and 61.3 million bookings in 3 years. Currently, Swvl has plans to launch the service in 22 European countries (Swvl, 2021). (ii) Via (ridewithvia.com) which provides a software package to different cities transit authorities to operate services similar to Jetty, and (iii) MOIA (moia.io) which operates in Germany with a similar scheme to Jetty, but only in vans and the company owns the 40 vehicles. The company defines itself as app-based collective transport service (Onésimo Flores Dewey, 2019).

2 https://developers.google.com/transit/gtfs/.

3 www.conapo.gob.mx/en/CONAPO/Indice_de_marginacion_urbana_2010 accessed on 15 February, 2022.

4 swvl.com, accessed 15 February, 2022.

4. Data analysis

4.1. Survey data

We collected 3050 responses, from which 2484 responses were complete or partially complete. Only 1118 responses provided correct and complete home and work zip codes information used to geocode the subsequent home and work addresses; therefore, we used them (N =1118) for the modeling process. We statistically compared the distribution of all variables between the subsample (1118) and the total sample (2484) to ensure the subsample's use representability adequacy. We did statistical testing for the distribution of two samples, with no statistically significant difference was observed.

4.1.1. Users' profile, and general travel behavior

Table 1 shows the sociodemographics attributes distribution of the sample and their counterpart available levels in CDMX. The sample resemble the general characteristics of shared mobility users of being young, highly educated (Grahn et al., 2019; Young and Farber, 2019; Tirachini, 2019; Shaheen et al., 2017; Dias et al., 2017; Shaheen et al., 2016b), high income level (Grahn et al., 2019; Tirachini, 2019; Dias et al., 2017; Mueller et al., 2015; Hupp, 1981), high car ownership rate (Shaheen et al., 2016b) with a larger rate of full-time employees (Dias et al., 2017; Gehrke, 2018; Kim et al., 2015; Hupp, 1981) compared to the average population. 90% of the sample has higher-education degree compared with only one-third of the city population. The sample average income is around 20K MXN[5] compared to 10K MXN as the average CDMX dwellers income. 81% of the respondents have at least one car/household compared to the city average of 0.53 cars/household (INEGI, 2015; Información estadística para el futuro académico y laboral en México, 2020). Several studies observed the role of gender in determining the use of shared mobility, where male users are the most frequent users (e.g. Degele et al., 2018; Howe and Bock, 2018; Raux et al., 2017; Shaheen et al., 2017).

Users specified their frequent use for the most common modes in CDMX, covering PT modes, private transport and shared mobility modes. Fig. 1 shows the frequency of use for the top ten modes reported by the users; the least used modes are shared Scooter, bikesharing, and suburban train. The previous use pattern could be because the scooter sharing was recently introduced at the time of the survey, and suburban train geographical coverage is limited. In the case of bikesharing, the majority of home and work locations for the users are in suburban areas outside of CDMX boundaries, which does not have the available infrastructure for bikes and bikesharing stations,[6] Fig. 3 shows home and work locations in reference to CDMX boundaries. Interestingly, the most used modes are e-hailing (which includes ride-hailing and taxi e-hailing apps) followed by metro. The high ownership of cars is also reflected in the users' travel behavior as using the car as a driver or as a passenger is among the top used modes by Jetty's users. When comparing the user of e-hailing to taxi, it is to be observed that 36% of Jetty passengers use e-hailing at least once a week compared to 15% in the case of taxi, which is likely not the case of the average city population where the use of e-hailing is lower than the use of the taxi, at least up to 2017 (INEGI, 2017). Also, 28% the users use shared-app-vehicles at least once a week; these previous observations indicate that frequent shared mobility users are more open to adopting the different shared services than the rest of the population. We further investigated this use pattern by applying factor analysis as discussed in the following section. Also, users' travel patterns per gender were investigated, with no statistically significant difference was observed, except for the car, where males are more frequent drivers than females, and females use the car as passengers more than males.

4.1.2. Modes replaced by Jetty and modes used to access and egress Jetty

Users specified up to three modes that they would have used to replace their latest Jetty trip, as well as up to two modes they used to access and egress from their latest Jetty trip. The results show the convenience of Jetty replacing multi-modal trips. 74% of the latest trips would have taken place in at least two modes, on average 2.1 modes/trip/user; showing the convenience the service provide in terms of number of transfers savings. Also, 1% of users specifies that they would not have made the trip if Jetty was not available; this number indicates Jetty has a marginal effect on inducing travel demand and allowing the performance of activities. The top five replaced modes are metro (53%), bus/Camion (32%), car as a driver (25%), e-hailing (24%), and microbus (18%). The replaced modes show that Jetty attract users from PT, similar to other shared mobility services (Moody et al., 2021; Alonso-González et al., 2020; Tirachini, 2019; Tirachini et al., 2020; Lavieri and Bhat, 2019; de Souza Silva et al., 2018). On the other side, Jetty also attracts users from small vehicles such as private cars and e-hailing.

Users' access and egress modes analysis reflects Jetty policy in locating pick-up and drop-off locations based on actual demand and users' requests. 88% of the users access Jetty using one mode, and 94% egress the service using one mode. 38% of the users who access the service with one mode use active mobility (walking or biking), while 57% egress the service using active mobility. This analysis also indicates the potential of dynamically relocating pick-up and drop-off locations for solving the last mile dilemma.

4.1.3. Users' activities during Jetty trips, and reasons to use Jetty

Users were asked to specify up to three activities that they do while they travel in a Jetty vehicle; the most specified activities are sleeping, using the smartphone, and looking out of the window, Table 2 shows the summary for the top five activities per gender. There is no significant difference between the genders for the different activities except for (i) sleeping, where women outnumbered men by 7%, which might reflect the sense of security women experience while using Jetty, which they do not experience in CDMX PT, (ii) and reading for pleasure, where males outnumber females by around 6%.

[5] One US Dollar = 19 Mexican pesos (MXN) at the time of the survey application, July 2019, source: xe.com.

[6] https://www.ecobici.cdmx.gob.mx/en/stations-map, accessed 4/7/2021.

Table 1
Users sociodemographic summary.

Variable	Levels	Survey (Pct.%)	CDMX
Age			
	18–25	12.9%	Middle Age 33 Years
	26–35	47.1%	
	36–45	26.5%	
	46 and older	12.8%	
	Missing	0.8%	
Gender			
	Female	50.5%	
	Male	49.6%	Ratio Male:Female 1:1.11
	Missing	0.0%	
Household Size			
	1	4.7%	
	2	23.4%	
	3	25.3%	Average household size 3.2 unit
	4 and more	43.0%	
	Missing	3.6%	
Personal Income, Pesos (MXN)			
	Less than 10,000	9.7%	
	10,000–30,000	57.1%	Average monthly income 10,000
	30,000 and more	19.1%	
	Missing	14.1%	
Driving License			
	Yes	80.2%	
	No	19.8%	
	Missing	0.0%	
Cars in Household			
	0	18.8%	
	1	46.5%	
	2 and more	34.7%	
	Missing	0.0%	
Education level			
	Masters or Doctorate	15.9%	High Education 32.1%
	Bachelor or professional degree	74.1%	Upper Secondary 26.6%
	Technical career	4.9%	Basic Schooling 38.9%
	High School or Baccalaureate	4.3%	No specific degree 0.3%
	Other	0.4%	Illiterate 1.5%
	Missing	0.5%	
Employment Status			
	Full time job	89.7%	
	Part time job	2.7%	Economically Active 95.5%
	Other	7.6%	
Total = 1118			Population = 8,811,266 (2017)

Table 2
Top five disaggregated activity per gender.

Activity	Female	Male
Sleeping	79%	77%
Use Smartphone	72%	72%
Look out of the window	35%	32%
Reading for pleasure	19%	26%
Talk on the phone	16%	13%
Total = 1118	564	554

Concerning the reasons to use Jetty, users could specify up to six reasons from a choice set consisting of fourteen options for why they use Jetty. The top three reasons to use Jetty are booking the seat, security against theft, and saving in travel time, which were chosen by around two-thirds of all the users. These reasons reflect the problems of PT in a crowded city like CDMX or, in other words, the factors that push commuters from PT use to Jetty use are mostly related to comfort and security. The gender distribution for the different reasons is almost balanced for all reasons except for two: (i) security against harassment. Females reported this reason six times more than males, which might reflect the increasing gender-based violence problem in public transportation in

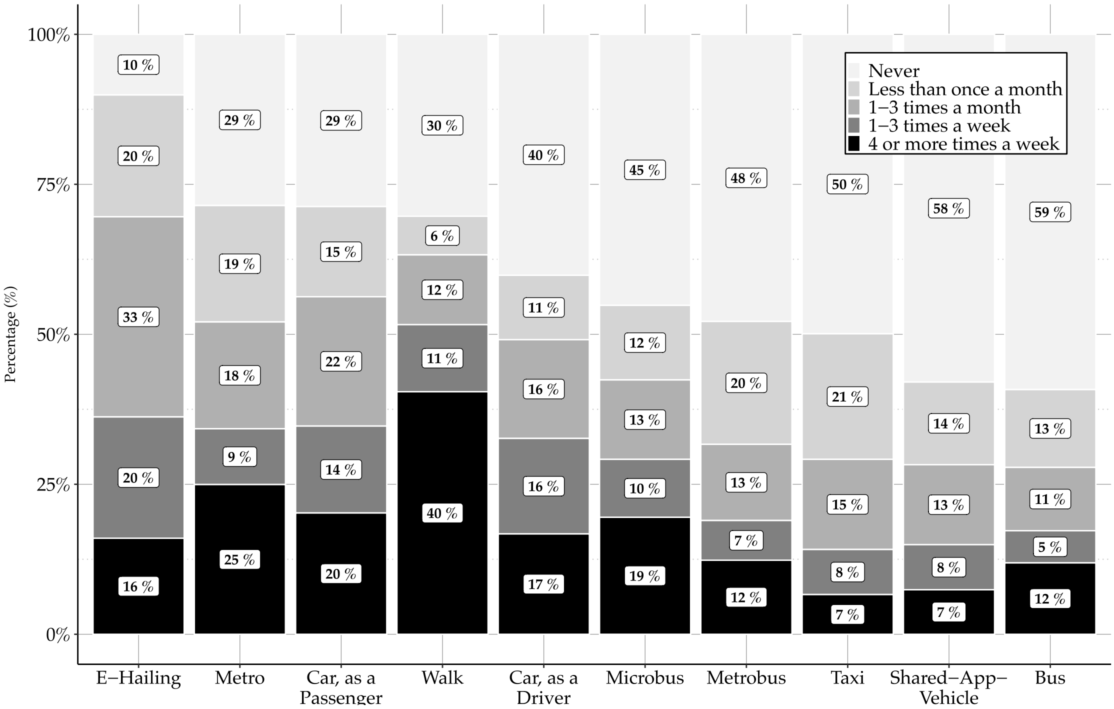

Fig. 1. Top ten used mode, use frequency distribution.

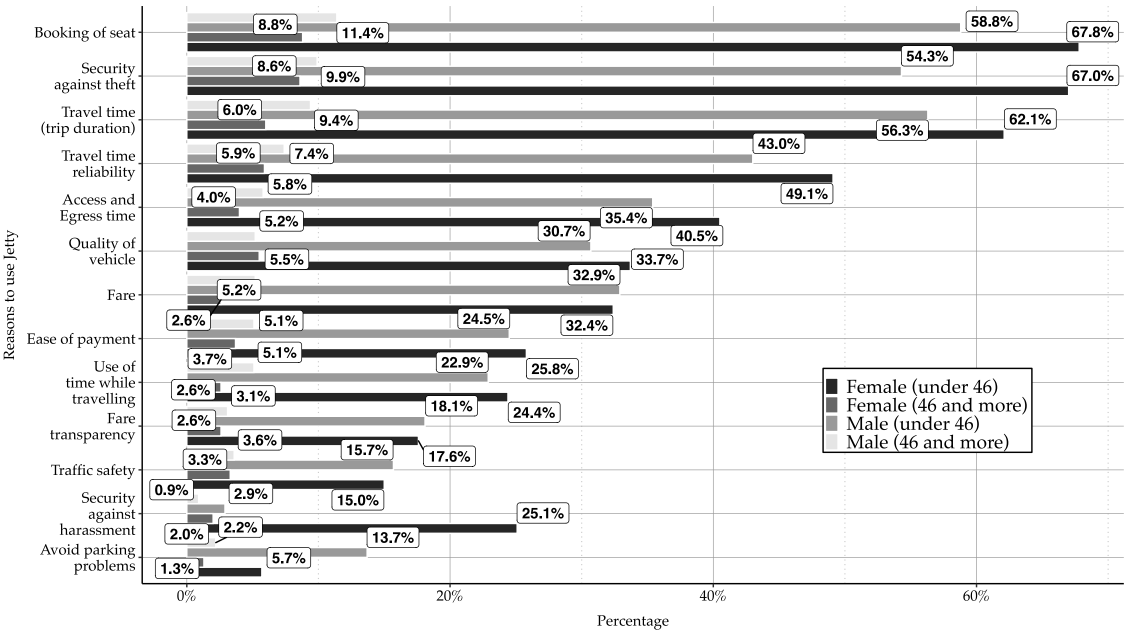

Fig. 2. Users' reasons to use Jetty per gender.

CDMX (Rivadeneyra et al., 2015; Mejía-Dorantes and Soto Villagrán; Dunckel-Graglia, 2013; Vilalta, 2011). (ii) The second difference is in avoiding parking problems; males were twice as likely as females to report this reason to use Jetty. This could be because males use cars as drivers more than females, and they have higher driving license ownership rates, as shown in Fig. 1 and Table 1.

Fig. 2 shows the distribution of the activity per gender, and age groups. Phi coefficient of correlation for binary variables (Ekström, 2011) was calculated for the variables of reasons to use Jetty and activities during Jetty trip, 23 variables, to investigate if

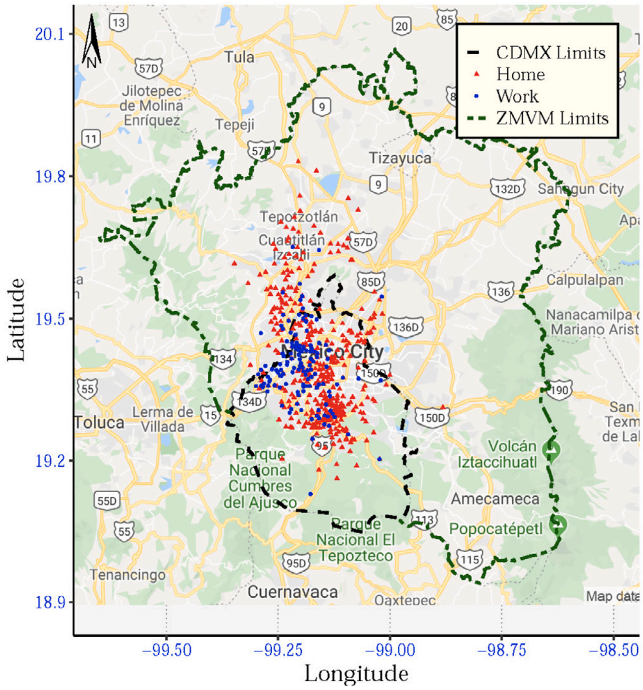

Fig. 3. Jetty users home and work locations.

Table 3
Willingness to walk time summary statistics.

Willingness to Walk	Count (Pct.%)
<4 min	54 (4.8%)
4–6 min	169 (15.1%)
7–10 min	403 (36.0%)
11–15 min	299 (26.7%)
16 ≥ min	193 (17.3%)
Total	1118 (100.00%)

there is any correlation between any pairs of the different variables. The estimated phi coefficient was less than 0.1 between all variables, indicating no association between choosing any pair of variables.

4.1.4. Users' willingness to walk, and city residency

To investigate users' willingness to walk to the nearest Jetty station, we asked them to specify their preferred walking time to the nearest station on an interval scale. One-fifth of users specified that they are willing to walk up to 6 min, while 62% of the users expressed their willingness to walk between 7–15 min to access Jetty, Table 3 shows the summary of the stated times. We investigated the impact of the willingness to walk on the different use characteristics, as discussed in detail in the next section. We believe that as Jetty is not a door-to-door service, the willingness to walk to the pick-up point would play a significant role in deciding to use the service or not.

Fig. 3 shows the home and work locations as specified by the survey respondents. We used Google[7] maps API to geocode the provided zip codes for home and work locations. 80% of the users reside within CDMX geographic limits, and the rest of the users reside outside the CDMX limits but within the ZMVM boundaries.

4.2. Jetty databases

The second source of information that we analyzed were the Jetty trip database. The trip database contained individual trips details for the survey participants for the seven months prior to the survey launching date; 54,175 Jetty trips performed by the 1118 survey respondents.

[7] Google.com/maps.

Table 4
Jetty relative use frequency.

Use rate	Users Pct%	% Morning trips (±SD)
Less than once a month	12.6%	45.4% (±45.7%)
1–3 times per month	22.9%	44.5% (±36.1%)
1–3 times per week	28.4%	52.2% (±32.1%)
4 or more times per week	36.1%	57.0% (±16.7%)
Total = 1118 (100%)		

Table 5
Trip characteristics by vehicle type.

Vehicle	Distance km ($\pm SD$)	Duration min ($\pm SD$)	Fare MXN ($\pm SD$)
Bus	24.7 (±2.58)	45.7 (±4.7)	40.2 (±10.9)
Van	26.1 (±10.7)	48.2 (±19.8)	62.8 (±22.0)
Caddy	25.8 (±4.59)	47.6 (±8.5)	74.7 (±12.5)
Taxi	19.3 (±1.92)	35.8 (±3.5)	58.8 (±13.2)

54,174 trips.

4.2.1. *Jetty use frequency, and timing*

Firstly, we analyzed the individual Jetty use frequency; on average, users did (1.7 ± 2.2) trips per week in the referred seven-month period. To compare Jetty use to the general travel behavior, we calculated the relative frequency of use frequency by accounting for the time span from the first recorded trip to the latest trip, per user. We opted to use this relative frequency of use to normalize the different dates in which passengers start to use the service. Table 4 shows the four categories of frequency of Jetty use: (i) Less than once a month (ii) 1–3 times per month, (iii) 1–3 times per week, and (iv) 4 or more times per week.

The travel demand in CDMX morning hours is almost double the evening peak hour demand (INEGI, 2017). Also, Therefore, we calculated the percentage of morning trips (trips before noon time) per user to model their impact on Jetty use. Table 4 shows more frequent Jetty users perform a larger proportion of morning trips by Jetty (relative to the total Jetty use). This might be related to the fact that commuters tend to have a higher value of travel time savings in the morning, before reaching the workplace, due to the arrival time constraints (Paleti et al., 2015). The deteriorated traffic condition in the morning peak in Mexico City may act as a strong encouragement to use Jetty more at this period, if it saves time relative to other travel alternatives. However, only 31% of the users who have been doing the majority of their trips during the morning hours (50% or more of their trips are done before noon) chose the reason to use Jetty is travel time reliability. Also, there was no statistically significant difference in trip duration for the different investigated users groups.

4.2.2. *Trip characteristics*

Jetty trips are performed in four vehicle types: (i) taxi, three-seat capacity, (ii) caddy, six-seat capacity, (iii) van, 13–19 seat capacity, and (iv) bus, 41–45 capacity. The majority of Jetty's trips (68%) materialize in buses, 30% in vans, and the rest in taxis and caddy. The main differences between these categories are the capacity and price: the taxi is the smallest and most expensive service, whereas the bus is the largest vehicle with the lowest fare. In some cases and after filling all the booked seats, extra users can stand in the corridor of the buses, which could stimulate the feeling of using PT. Trip characteristics by vehicle type are not significantly different except for taxis, which show trips that are shorter and more expensive compared to larger vehicle types (see Table 5).

4.3. *GTFS files*

The third source of information is the GTFS files. GTFS files were included in the analysis to study the synergy between users' home locations, available public transport modes, and the use of Jetty. The files were retrieved from the open mobility data platform.[8] The Nearest Neighbor search algorithm was implemented to identify the closest station of each of the public transport modes available in the GTFS files to each home location. Afterward, the headway in the nearest station for each mode is assigned for the corresponding users, and the direct distance to the nearest station is calculated. Table A.14 shows the summary statistics for the headway and distance for the different modes for the partial sample users. The analysis of the GTFS files conforms to the properties of the public transport network in CDMX. For example, the average mean distance to the nearest suburban train is significantly larger than the other modes since the suburban train line is limited to the north of the city. Moreover, the broad coverage of the RTP (BRT) network is evident[9], where the average access distance is 1.9 km, which is the smallest distance compared to all other modes.

[8] transitfeeds.com.
[9] metro.cdmx.gob.mx, accessed on 10/4/2021.

Table 6
EFA results.

Mode frequency of use	Factor 1	Factor 2
Metro	0.64	
Metrobus	0.42	
Light-Rail	0.58	
Trolleybus	0.60	
RTP	0.60	
Bus	0.50	
Minibus	0.66	
Combi	0.58	
Bicycle		0.52
Bikesharing		0.87
Shared-Scooter		0.70
Walk		0.45
Factor interpretation	**PT-Users**	**MM-Users**
Proportion Var	0.23	0.16
Cumulative Var	0.23	0.39

5. Modeling process

5.1. Exploratory Factor Analysis

Exploratory Factor Analysis (EFA) was performed on the frequency of different modes using Likert data, Fig. 1, to infer the individual latent construct between the different modes use patterns. Before running the EFA, the initial hypotheses were built. The EFA results are expected to reveal three factors that indicate the use of PT and paratransit as the first factor, the use of taxi and private car as the second factor, and the third factor is the use of micro-mobility. The initial factors number was estimated using a scree test (Ledesma and Valero-Mora, 2007), and considering the initial Hypotheses. The polychoric correlation was used to calculate the EFA as it was preferred over the commonly used Pearson correlation with ordered nominal data (Holgado-Tello et al., 2010). Starting from 20 variables, only factors that explain at least ten percent of the data variability were kept; therefore, variables such car use and taxi use frequency are not presnet in the final factors (Tyrinopoulos and Antoniou, 2008). Twelve variables and two factors capturing 39% of the data variance were estimated. The estimated EFA revealed two factors represent two user groups with two distinct travel patterns. (i) The first factor is the frequent PT and paratransit users (referred to as PT-Users). (ii) The second factor is micro-mobility and shared-micro-mobility users (refereed to MM-users); Table 6 shows the EFA analysis results.

5.2. Modeling the factors impacting the shift to Jetty

This model aimed to investigate which factors affect the user's choice to shift from the originally used modes to Jetty. This model answers the first research question. A binary choice model and an HCM were estimated to investigate the questioned factors. The main objective to use Hybrid Choice Models is to integrate the latent variable model to the choice model by integrating the users' cognitive behavior and attitude, into the choice model, which create a realistic choice behavior (Ben-Akiva et al., 2002; Bolduc and Alvarez-Daziano, 2010). For the subject model, the answer to which modes would have been used to replace the latest Jetty trip was used as the dependent variable. Modes were grouped into four groups that have common operational and usage attributes:

- Group **A**: Motorcycle, Car as a driver or passenger (**Private modes**)
- Group **B**: Ride-hailing, taxi e-hailing and taxi (**Taxi**)
- Group **C**: Shared taxi, Minibus, Combi, and Camion (**Paratransit**)
- Group **D**: Metro, Metrobus, Ecobus, and Suburban train (**PT**)

The reported modes to replace Jetty trip were coded to one of the respective four categories, and if two modes were in the same group, they were coded only once (for instance, if a Jetty trip replaces a trip previously made in Metro and shared taxi, then it was considered in Groups C and D, and if the replaced modes were Metro and Metrobus, it was considered in Group D only). Eighty-one percent (81%) of the trips were performed in one or two of the main modes categories. The rest of the trips (17.5%) were completed in three different groups noting that at least one of the three modes belongs to group A or B. Table 7 shows the trips summary details, and Table 8 shows the details of the trips that were done in three different mode categories.

The dependent variable was coded as a binary variable set to be equal to zero if a trip was completed in groups (C, D, and C+D), and it was set to one otherwise. The dependent variable defines the choice between the PT and paratransit trips, and on the other side, the trips made, or partially made in private modes and taxi, will be referred to it in the following sections as car trips.

The choice model was estimated without the inclusion of latent variables results. After estimating the choice models, the latent variable were added, and their impact on the model goodness of fit was tested. Only one latent variable, the frequent use of PT, was significantly different from zero. Fig. 4 shows the full path diagram of the final model.

Table 7
Combined modes replacing last Jetty trip summary statistics.

Category	Count (Pct.%)	Category	Count (Pct%)
A (Private Modes)	140 (12.5%)	A+C	20 (1.8%)
B (Taxi)	62 (5.5%)	A+D	37 (3.3%)
C (Shared taxi, Collective Services)	67 (6%)	B+C	33 (3%)
D (PT)	96 (8.6%)	B+D	46 (4.1%)
C+D	350 (31.3%)	Three different modes (Table 8)	196 (17.5%)
A+B	57 (5.1%)	No Trip	14 (1.3%)

Total = 1118.

Table 8
Trips in three different modes summary.

Category	Count (Pct.%)	Combination	Count (Pct.%)
A	112 (57.1%)	A+B+C	13 (6.6%)
B	129 (65.8%)	A+B+D	32 (16.3%)
C	164 (83.7%)	A+C+D	67 (34.2%)
D	183 (93.4%)	B+C+D	84 (42.9%)

N = 196.

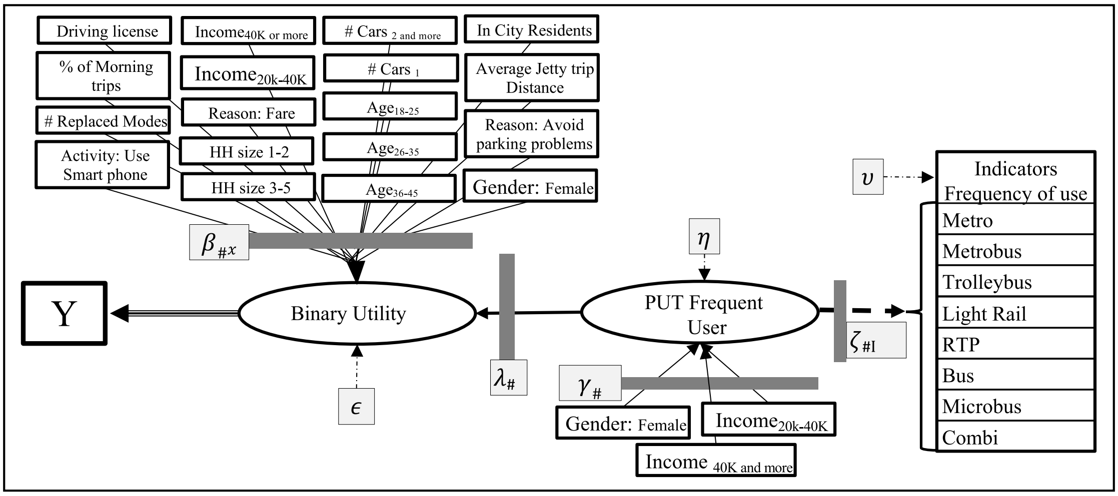

Fig. 4. Shift to Jetty HCM full path diagram.

Table 9 left side shows the estimation results for the HCM, and the right side shows the reduced choice model, and Table 10 shows the estimation of the latent model part of the HCM. The HCM was estimated using classical integration estimation.

The estimated model shows that female, young users, small-sized households (one-to-two-person), high-income groups, with driving license, and with cars in the household are more likely to shift to Jetty from car trips compared to other users groups. These findings match some of the previous research results regarding the general profile of shared mobility users being wealthier, younger than the average population. The model shows that people who use their smartphones during Jetty trips are more likely to shift from car trips to Jetty, which indicates the preference of multi-tasking by these users. Also, people who specified using the service due the fare and to avoid parking problems are more likely to shift from car trips. The characteristics of the replaced mode impact the shift decision. The larger the number of modes that a Jetty trip is replacing, the larger the likelihood that a car was involved in the original chain. This may be attributed to the fact that – in this case – car was not used for a convenient, door–to–door trip, but instead as a first-/last-mile in a longer chain (likely including search for parking and other annoyances). Users who make more trips using Jetty in the morning (before noon) are more likely to shift from car trips to Jetty. Users' home geographical location impacts the choice to shift, as the estimated negative coefficient of the "In City" variable shows that residents of the city are less likely to shift from car trips to Jetty. Also, Jetty trip attributes impact the shift decision; the longer the average Jetty trip distance per user, the less likely the user is to shift from car trips.

Table 10 shows the measurement model part of the latent variable model. The measurement model estimated positive coefficients (ζ) show that the higher the levels of the answer (the more frequent the use), the more the use of the PT in general, which is intuitive. Also, Table 10 shows the structure equation part of the latent variable model. Coefficients of the structure model (γ) need to be explained along with the measurement model. For gender, females' negative sign coefficients have a negative impact on the latent variable compared to males; in other words, females are less frequent users for PT, and therefore, more likely to shift to Jetty from

Table 9
Shift to Jetty from car-based modes HCM and binary logit model results.

Variable	HCM Model		Choice Model	
	β (P-value)	Rob.Std. Error	β (P-value)	Rob.Std. Error
Intercept	−4.45 (0.00)	0.69	−3.74 (0.00)	0.59
Gender: Female (vs Male)	0.07 (0.71)	0.18	0.50 (0.00)	0.16
Age between 18 and 25 (vs age 46 and older)	1.20 (0.00)	0.35	1.12 (0.00)	0.31
Age between 26 and 35 (vs age 46 and older)	0.57 (0.04)	0.28	0.47 (0.06)	0.25
Age between 36 and 45 (vs age 46 and older)	0.57 (0.05)	0.29	0.46 (0.07)	0.26
Household size between 1–2 (vs household size 6 and more)	0.64 (0.07)	0.35	0.78 (0.01)	0.29
Household size between 3–5 (vs household size 6 and more)	0.33 (0.29)	0.31	0.40 (0.13)	0.26
Personal Income between 20K–40K (vs 20K or less)	0.39 (0.05)	0.20	0.71 (0.00)	0.17
Personal Income 40K or more (vs 20K or less)	0.76 (0.01)	0.31	1.47 (0.00)	0.28
Driving license Availability yes (vs no)	0.76 (0.00)	0.22	0.70 (0.00)	0.20
In City Resident (vs no)	−0.46 (0.06)	0.24	−0.56 (0.01)	0.22
#No of cars in household = 1 (vs zero cars)	0.72 (0.00)	0.26	0.91 (0.00)	0.22
#No of cars in household = 2 or more (vs zero cars)	0.64 (0.02)	0.28	1.02 (0.00)	0.24
#No of modes replaced by Jetty	0.55 (0.00)	0.12	0.22 (0.02)	0.09
Average Jetty trips distance	−0.33 (0.00)	0.11	−0.31 (0.00)	0.10
Pct (%) of morning trips	0.54 (0.02)	0.24	0.66 (0.00)	0.22
Activity: use smart phone	0.32 (0.09)	0.19	0.37 (0.02)	0.16
Reason: fare	0.58 (0.00)	0.18	0.55 (0.00)	0.16
Reason: Avoid parking problem	0.54 (0.04)	0.26	0.52 (0.02)	0.23
LV: Frequent PT user (λ)	−1.13 (0.00)	0.14	–	–
$\rho^2_{Adjusted}$	**0.10**		**0.12**	

P-values are reported in parentheses are based on the robust standard errors, used to control for heteroscedasticity that might exist.

Table 10
Shift to Jetty from car-based modes latent variable model.

Structure Model (Frequency of PT Use)	ζ (P-value)	Rob.Std. Error
Gender:Female	−0.51 (0.00)	0.08
Personal Income between 20K–40K (vs 20K or less)	−0.52 (0.00)	0.09
Personal Income 40K or more (vs 20K or less)	−1.07 (0.00)	0.13
Measurement Model (Frequency of PT Use)	γ (P-value)	Rob.Std. Error
Indicators		
Frequency of Metro use.	1.40 (0.00)	0.12
Frequency of Metrobus use	0.71 (0.00)	0.09
Frequency of Light-Rail use	1.27 (0.00)	0.14
Frequency of Trolleybus use	1.37 (0.00)	0.20
Frequency of RTP use	1.34 (0.00)	0.13
Frequency of Bus use	0.99 (0.00)	0.10
Frequency of Microbus use	1.33 (0.00)	0.11
Frequency of Combi use	1.26 (0.00)	0.12

P-values are reported in parentheses are based on the robust standard errors, used to control for heteroscedasticity that might exist.

a trip previously made fully or partially by car. For the income, the estimated coefficient negative sign shows that high-income groups are less frequent PT users, and the income level 40k or more have the most impact on the LV. The thresholds between the different levels of the indicators (τ_p) are only reflecting the threshold's orders, which is why their estimation results are not shown. In the choice model, (λ) represents the impact of the latent variable (α) on the choice model. The latent variable impact on the model can be interpreted as the latent variable (frequent PT users) that are less likely to shift from car trips to Jetty. The coefficient of the latent variable in the choice model is the second-highest coefficient, which shows the LV impact on the choice. Inclusion of the attitudinal factors, LV, reduces the magnitude of the sociodemographic variables estimated coefficients, which confirms that sociodemographic variables act as representative for latent attitudes; the same phenomenon was observed in similar studies using similar modeling techniques (Alemi et al., 2018a).

We used the rho-squared-adjusted ($\rho^2_{Adjusted}$) to compare the goodness of fit of the HCM and the restricted choice model. The HCM has a lower ($\rho^2_{Adjusted} = 0.10$) than the reduced choice model ($\rho^2_{Adjusted} = 0.12$), indicating that the reduced choice model fits the data better. However, the HCM provides extra insights on the role played by the latent variable. compensates for the reduced fit as the primary use of this model is to investigate the variable affecting the shifting process, and the model will not be used in any prediction. Ben-Akiva et al. (2002) used the previous evaluation methodology.

Table A.15 shows the summary of the model's significant variables against both levels of the dependent variable.

5.3. Modeling factors influencing services type choice

This model investigated the factors influencing the choice between the different vehicles types, as Jetty trips are available in four vehicular categories: taxi, caddy, van, and bus. We assigned each user the most used vehicle type based on their actual use retrieved from the Jetty trips database. The percentage of trips per vehicle type for each user was calculated, and the vehicles with the highest number of trips were assigned as the most frequently used vehicle for each user. Most users (98%) performed their trips in buses or vans; therefore, the factors affecting the choice between bus or van were investigated. Other users using taxi and caddy were excluded from the analysis due to their limited sample size; therefore, the number of observations used for this model was 1080 instead of the total sample of 1118. There are two main reasons behind comparing the factors impacting the choice between buses and vans: vans are smaller in size (almost half the bus capacity on average), with a larger level of service and convenience as valued by some users, and the van ticket is more expensive than the bus ticket. A binary logit model was developed to investigate the factors affecting the choice between the two service types. The dependent variable was a binary variable equal to zero when the most frequently used vehicle is a bus and one when the most frequently used vehicle is a van. Table 12 shows the estimated coefficient of the final model.

Four sociodemographic attributes, gender, household size, income, and employment status, impacted the choice between the different vehicle sizes. Females, full-time employees, and high-income groups are more likely to use vans, and small-sized households are more likely to use the bus. This finding is related to the facts that buses have lower fares than vans, but vans are closer in quality attributes to a private car. The estimated coefficients show that users who work during the trip are more likely to use the van, and those who talk on the phone during the trip are more likely to use the bus. These findings also comply with the nature of the two-vehicle types. Four reasons to use Jetty are significantly different from zero in explaining the preference for vans or buses: the booking of the seats, the ease of payment, security against theft, and fare. The estimated coefficients show that users who appreciate the booking of seats and the ease of payment as qualities of the Jetty service are more likely to use the bus over the van, and users who use Jetty for security against theft and fare are more likely to use vans over buses. The estimated coefficient of the willingness to walk to the access point shows that the people willing to walk longer distances opt to use the bus over the van. This finding complies that access distanced to buses is on average longer than average access distances to vans. Users who access or egress the service by walk or bike are more likely to use the van over the bus. This could be because the access distances to the van are, on average shorter than the access distances to the bus. The estimated coefficient shows that users who make more trips using Jetty in the morning (before noon) are more likely to use a van.

The longer the Jetty trip, the more likely it is made using a van. This finding complies that the level of convenience of using a van is higher than using a bus. The relative Jetty use frequency estimated coefficients show that the most frequent Jetty users also have a larger rate of the bus traveling when booking Jetty trips, which might be explained by the lower average price of bus trips relative to van trips. Finally, the larger the headway (time interval between two consecutive trains) in the nearest metro station, the larger the adoption of buses over vans, which is interpreted as buses being a closer substitute of PT than vans; which can be attributed to the cheaper bus trip cost compared to van's trip cost.

EFA results were used to investigate the latent variables (travel attitudes) impact on the service choice preference; however, no acceptable results were obtained trying multiple structure and choice model specifications and different combinations.

Additional analysis was performed to assess and verify the impacts of the significant variables on the choice model. Table 11 shows the summary statistics for the significant parameters, and it shows that the average trip distance is almost equal for buses and vans users. Moreover, access and egress distances for van users are shorter. The metro headway is shorter by half a minute for the van users due to their geographic location distribution. Moreover, Table 11 shows that bus users are more willing to walk a long time to access Jetty.

5.4. Modeling factors impacting the frequency of Jetty use

In this model we explored the factors that have an effect on the frequency of Jetty use. An ordinal Logistic Hybrid Choice Model (HCM) and an Ordinal Logit Model (OLM) were developed to investigate the factors affecting the Jetty use frequency.

The dependent variable was set as the relative use frequency for each user. The variable was calculated by dividing the number of Jetty trips over the period between the first and last rides for each user recorded in the retrieved service use dataset. Table 4 shows the summary of the dependent variable.

We investigated the impact of the two latent variables (estimated from the EFA results), on the frequency of use. Both latent variables were proven to be significantly different from zero. Fig. 5 shows the full path diagram for the HCM.

In the OLM, the only sociodemographic attribute that impacts the service use frequency is employment: full-time workers are more likely to use Jetty more frequently than other employed categories. Regarding time use while traveling, users that work, read for pleasure, sleep or study are more likely to be frequent Jetty users. The perceived reliability of travel time and the quality of vehicles are attributes appreciated by frequent Jetty users, while people that use Jetty because of their fare tend to be less frequent users, which is intuitive as Jetty is not a cheap service compared to PT (but it is cheaper than ride-hailing). The interaction term (Female x Reason: Security against Harassment) represents the female users who use the service because of its security against harassment. The estimated coefficient shows that this user group is more likely to use the service more frequently. People performing more trips in the morning are more likely to use Jetty more frequently. Trip distance tends to increase the use of Jetty, which is related to the convenience introduced by this service, as more extended trips could increase transfers and longer travel time if done in modes other than Jetty. The longer the access or the egress distance to or from Jetty, the less frequency the person uses Jetty.

Table 11
Service choice model significant variables summary.

	Bus	Van		Bus	Van
Categorical variable	Count (Pct.%)	Count (Pct.%)	Variable	Count (Pct.%)	Count (Pct.%)
Age			**In City Residence**		
Between 18 and 25	98(14.78%)	44(10.55%)	No	19(2.87%)	203(48.68%)
Between 26 and 35	280(42.23%)	220(52.76%)	Yes	644(97.13%)	214(51.32%)
Between 36 and 45	184(27.75%)	106(25.42%)	**Willingness to Walk to access point**		
46 or More	97(14.63%)	42(10.07%)	10 min or less	322(48.57%)	273(65.47%)
Missing	4(0.6%)	5(1.2%)	More than 10 minutes	341(51.43%)	144(34.53%)
Gender			**Activity Working**		
Female	331(49.92%)	218(52.28%)	No	587(88.54%)	345(82.73%)
Male	332(50.08%)	199(47.72%)	Yes	76(11.46%)	72(17.27%)
Household Size			**Activity Talk on Phone**		
Between 1 and 2	148(22.32%)	149(35.73%)	No	555(83.71%)	368(88.25%)
Between 3 and 5	424(63.95%)	228(54.68%)	Yes	108(16.29%)	49(11.75%)
6 and More	68(10.26%)	23(5.52%)	**Reason Booking of Seat**		
Missing	23(3.47%)	17(4.08%)	No	159(23.98%)	135(32.37%)
Personal Income			Yes	504(76.02%)	282(67.63%)
20K or less	326(49.17%)	158(37.89%)	**Reasons Security against theft**		
20K–40K	204(30.77%)	138(33.09%)	No	210(31.67%)	123(29.5%)
40K or More	42(6.33%)	57(13.67%)	Yes	453(68.33%)	294(70.5%)
Missing	91(13.73%)	64(15.35%)	**Reasons Ease of Payment**		
Driving License			No	451(68.02%)	313(75.06%)
No	133(20.06%)	81(19.42%)	Yes	212(31.98%)	104(24.94%)
Yes	530(79.94%)	336(80.58%)	**Jetty Use rate**		
Cars in the Household			Less Than Once a Month	72(10.86%)	63(15.11%)
zero	124(18.7%)	72(17.27%)	1–3 Times per Month	138(20.81%)	104(24.94%)
1	305(46%)	202(48.44%)	1–3 Times per Week	190(28.66%)	120(28.78%)
2 or more	234(35.29%)	143(34.29%)	3 Times or More per Week	263(39.67%)	130(31.18%)
Education			**Numeric Variable**	Mean ± SD	Mean ± SD
Bachelor or higher	579(87.33%)	389(93.29%)	Average fare (MXN)	40.90 ± (11.75)	64.93 ± (17.06)
Other	84(12.67%)	23(5.52%)	Average Trip Distance (km)	24.38 ± (3.44)	25.18 ± (10.20)
Missing	00(00.00%)	5(1.2%)	Pct of Morning Trips (%)	48 ± (33)	54 ± (36)
Employment			Access Distance (Km)	3.18 ± (2.59)	2.70 ± (2.83)
Full time	579(87.33%)	387(92.81%)	Egress Distance (Km)	3.70 ±(3.16)	3.57 ±(3.64)
Other	84(12.67%)	30(7.19%)	Access Distance (Km)	3.18 ± (2.59)	2.70 ± (2.83)
Access to Jetty Modes			Metro Headway (sec)	239 ± (87.3)	203±(57.4)
Walk or Bike	188(28.36%)	204(48.92%)			
Other	475(71.64%)	213(51.08%)			
Egress from Jetty Modes					
Walk or Bike	312(47.06%)	295(70.74%)			
Other	351(52.94%)	122(29.26%)	N = 1080		

Also, the longer the headway of the nearest metro station, which indicates longer waiting times for the metro service, the more likely the person to use Jetty. Finally, the three thresholds between the four levels of the use rate are significantly different from zero, indicating a noticeable difference between these levels.

Table 13 shows the measurement model part of the latent variable model. The measurement model estimated positive coefficients (ζ) shows that the higher the levels of the answer (the more frequent the use), the more the use of the PT and micro-mobility in general. For LV1 (MM use), gender's negative sign indicates that females are less frequent users of MM. For the income, the base group is the high income group (40,000 MXN or larger), and the estimated negative coefficient shows that high-income groups are more likely to use MM compared to the low-income groups. LV2 (PT use), indicate that females are less frequent users of PT compared to male users. For the income, the reference group is the income group with 40k or more MXN, and the estimated positive coefficient shows that the lower-income groups are more likely to use PT compared with the larger income group. For the number of cars in the household, the reference category is two or more cars in the household. The positive coefficients show that households with no cars are more likely to use PT compared to the other categories. It is to be noticed that the income level less than 20k and no cars in the household have the most substantial impact on this latent variable. The latent variables impact on the model, can be interpreted as the latent variable (frequent PT users) reduces Jetty use, and the frequent micro-mobility latent variable increases Jetty use; however, the LV1 (MM users) is not highly significant. The adjusted-rho-squared- ($\rho^2_{Adjusted}$) for both models show that both HCM and OLM have similar goodness of fit, however, the HCM has the advantage of the extra insight it gives from the structure model part.

Table 12
Service choice binary logit model (use of van instead of bus).

Variable	β (P-value)	Rob.std. Error
Intercept	−2.74 (0.00)	0.57
Gender: Female (vs Male)	0.36 (0.03)	0.17
Household size between 1–2 (vs Household size 6 or more)	1.14 (0.00)	0.33
Household size between 3–5 (vs Household size 6 or more)	0.71 (0.02)	0.31
Personal income less than 20K (vs more than 40K)	−0.94 (0.00)	0.29
Personal income 20–40K (vs more than 40K)	−0.71 (0.01)	0.29
Employed full time (vs employment status other)	0.74 (0.01)	0.30
Access by walk or bike (vs other modes)	1.13 (0.00)	0.17
Egress by walk or bike (vs other mode)	0.65 (0.00)	0.18
Egress duration	−0.34 (0.01)	0.13
Pct. (%) of morning trips	0.46 (0.06)	0.25
Headway in the nearest metro station	−0.34 (0.00)	0.08
Average Jetty Trip Distance	0.33 (0.00)	0.09
Willing to walk more than 10 min. (Vs 10 or less)	−0.42 (0.01)	0.16
Activity: working	0.43 (0.06)	0.22
Activity: talk on phone	−0.51 (0.04)	0.25
Reason: booking of Seats	−0.43 (0.02)	0.18
Reason: ease of payment	−0.38 (0.04)	0.19
Reason: security against theft	0.44 (0.01)	0.18
Reason: fare	0.31 (0.07)	0.17
Use Frequency: Less than once a month (vs 4 or more times a week)	0.98 (0.00)	0.27
Use Frequency: 1–3 times a month (vs 4 or more times a week)	0.69 (0.00)	0.23
Use Frequency: 1–3 times a week (vs 4 or more times a week)	0.60 (0.00)	0.21
$\mathcal{L}(\beta_0)$		−627.99
$\mathcal{L}(\hat{\beta})$		−483.49
$-2[\mathcal{L}(\beta_0) - \mathcal{L}(\hat{\beta})]$		289.00
ρ^2		0.230
$\rho^2_{Adjusted}$		0.19
AIC		1012.97
BIC		1123.58

P-values are reported in parentheses are based on the robust standard errors, used to control for heteroscedasticity that might exist.

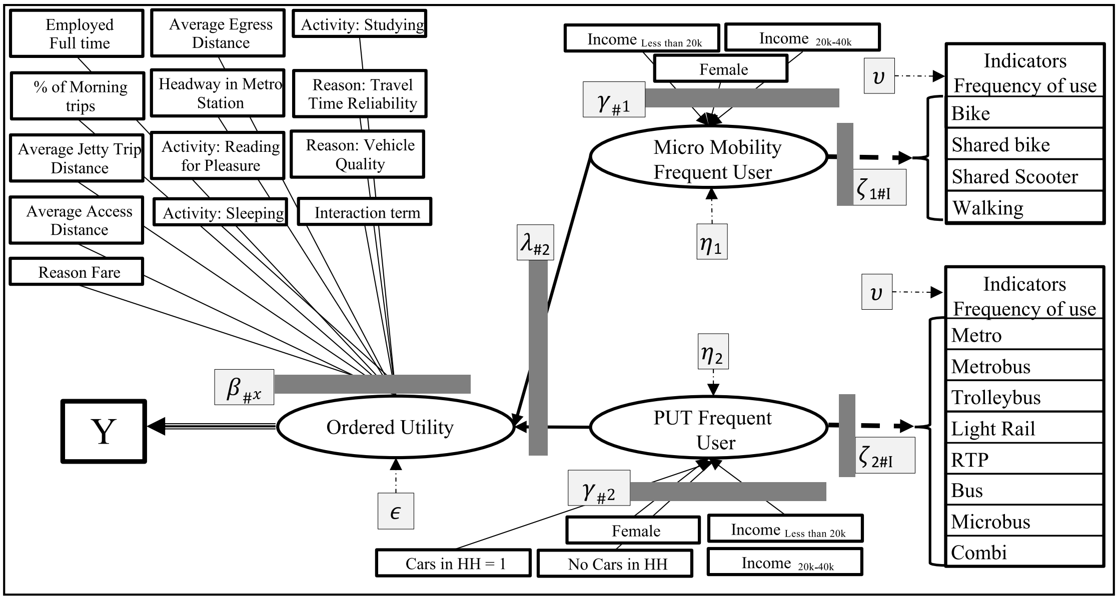

Fig. 5. Frequency of Jetty use, ordered HCM full path diagram.

Table 13
Jetty use frequency model results.

Variable	HCM		Choice Model	
	β (P-value)	Rob.Std. Error	β (P-value)	Rob.Std. Error
Employed Full time (vs others)	0.67 (0.00)	0.21	0.69 (0.00)	0.22
Percent % of Trips in Mornings	0.69 (0.00)	0.20	0.76 (0.00)	0.20
Average Jetty Trip Distance	0.21 (0.00)	0.07	0.2 (0.00)	0.07
Average Access Distance to Jetty	−0.13 (0.08)	0.07	−0.15 (0.03)	0.07
Average Egress Distance from Jetty	−0.29 (0.00)	0.06	−0.32 (0.00)	0.06
Headway in the nearest Metro Station	0.16 (0.01)	0.06	0.15 (0.02)	0.06
Activity Reading For Pleasure	0.37 (0.03)	0.17	0.34 (0.04)	0.16
Activity Sleeping	0.76 (0.00)	0.16	0.70 (0.00)	0.15
Activity Studying	0.91 (0.00)	0.31	0.85 (0.00)	0.26
Reason Travel Time Reliability	0.35 (0.01)	0.13	0.34 (0.01)	0.12
Reason Quality of Vehicle	0.37 (0.00)	0.13	0.33 (0.01)	0.13
Reason Fare	−0.38 (0.00)	0.13	−0.32 (0.01)	0.13
Interaction (Female X Reason Security Against Harassment)	0.36 (0.06)	0.19	0.34 (0.05)	0.17
LV1 Frequent MM user (λ_1)	0.14 (0.14)	0.10	–	–
LV2 Frequent PT user (λ_2)	−0.24 (0.00)	0.07	–	–
Thresholds				
Less Than Once a Month—1–3 Times per Month	−1.89 (0.00)	0.17	−2.01 (0.00)	0.17
1–3 Times per Month—1–3 Times per Week	−0.37 (0.02)	0.15	−0.51 (0.00)	0.15
1–3 Times per Week— More than 3 Times per Week	1.01 (0.00)	0.15	0.85 (0.00)	0.15
	$\rho^2_{Adjusted}$	**0.05**		**0.05**
Latent Variable Model				
Structure Model	Frequent MM Users		Frequent Pt Users	
	γ (P-value)	Rob.Std. Error	γ (P-value)	Rob.Std. Error
Gender: Female (vs male)	−0.48 (0.00)	0.11	−0.5 (0.00)	0.09
Personal Income Less than 20K (vs more than 40k)	−0.47 (0.00)	0.16	0.99 (0.00)	0.14
Personal Income 20K–04K (vs more than 40k)	−0.33 (0.03)	0.15	0.5 (0.00)	0.15
No Cars in Household (vs 2 or more cars)	–	–	0.93 (0.00)	0.10
Cars in Household = 1 (vs 2 or more cars)	–	–	0.43 (0.00)	0.09
Measurement Model	Frequent MA		Frequent PT	
Indicators	ζ (P-value)	Rob.Std. Error	ζ (P-value)	Rob.Std. Error
Frequency of Bike use	1.06 (0.00)	0.17	–	–
Frequency of Shared bike use	2.4 (0.00)	0.63	–	–
Frequency of Shared Scooter use	1.83 (0.00)	0.35	–	–
Frequency of Walk use	0.82 (0.00)	0.16	–	–
Frequency of Metro use	–	–	1.34 (0.00)	0.12
Frequency of Metrobus use	–	–	0.72 (0.00)	0.09
Frequency of Light-Rail use	–	–	1.19 (0.00)	0.17
Frequency of Trolleybus use	–	–	1.35 (0.00)	0.22
Frequency of RTP use	–	–	1.26 (0.00)	0.14
Frequency of Bus use	–	–	0.94 (0.00)	0.11
Frequency of Microbus use	–	–	1.17 (0.00)	0.13
Frequency of Combi use	–	–	1.15 (0.00)	0.12

P-values are reported in parentheses are based on the robust standard errors, used to control for heteroscedasticity that might exist.

6. Discussion, and study limitations

6.1. Discussion

The answer for the fourth research question was initiated by the EFA results; which revealed two factors explaining two underlying travel patterns: frequent PT and paratransit users, frequent micro-mobility, and shared micro-mobility users (Table 6). These factors demonstrate two distinctive user travel patterns and profiles, driven by the characteristics and preferences of the travelers, which shape their adoption of new services such as Jetty. User travel attitudes showed that frequent PT and paratransit users are less likely to be frequent Jetty users or to shift from PT and paratransit to Jetty. Also, frequent shared micro-mobility users are more likely to use the shared service, Jetty. This finding of travel attitudes opens the question of how to include non-adopter users in the service. In Jetty's case, the service is not used for luxurious purposes; for several reasons. 95% of the users specified their primary purpose of using Jetty is commuting to work. Also, the service connects the north of the city with limited access to formal jobs to the job concentration centers. The unavailability of the service would result in losses for the users in terms of loss of economic opportunities, loss in travel time if connections between several modes need to be made to travel, and increase in travel cost if ride-hailing or taxi used. Therefore, the service-non-adaptor should be widely investigated to understand the factors behind the non-adoption behavior, which would also help to identify strategies to reduce the chances of social inequity that is generally triggered by shared mobility services in their current state of development.

Sociodemographic characteristics of the population play a significant role in service adoption and use. We have found that gender, age, personal income, household size, and employment impact the service use and shift from other modes to Jetty. Females are more likely to shift to Jetty from car trips (trips that were done in cars, e-hailing, and ride-hailing or combination of these modes), and once Jetty users, they tend to prefer vans over buses. Also, females who use the service to avoid the risk of personal harassment in public transport tend to be more frequent Jetty users. The influence of age only appeared when moving from car trips to Jetty, where young users are more likely to shift to Jetty from car trips, which follows the data analysis findings and coincide with the general profile of shared mobility user. However, age did not impact the frequency of Jetty use.

Personal income is the most significant sociodemographic attribute in deciding on the shift from car trips to Jetty, service type, and use frequency. The high-income group is more likely to shift to Jetty, use a van (the most expensive service), and use the service more frequently. This finding makes it necessary to question the equity of the service and how it should be addressed on a broader scale to include all the income groups under the coverage of using such services, and to avoid the loss of economic opportunities. Small household sizes (1–2 persons) are more likely to shift from car trips to Jetty and use more expensive services (van). This finding matches the shared mobility users profile for other services in other cities, where single users are adopting the service more than the other population.

Full-time employees are more likely to use vans and use the service more frequently than other users; this also matches the profile of shared mobility users in other cities. The number of cars in the household impacts the shift to Jetty; as expected, users with cars in the household are more likely to shift to Jetty from car trips than other users; however, the car ownership rate does not directly impact the frequency of Jetty use. Having the ability to attract users from car trips and, as described earlier, approximately half of the disaggregated trips made in small-sized vehicles (passenger cars, taxis, and e-hailing) have the positive potential for reducing the VKT. The reduction of VKT using pooled rides service is possible, but it depends on several conditions such as using suitable vehicle sizes for the pooling service, the replaced modes, and modes used to access and egress from the service (Tirachini et al., 2020).

Trip distance is a significant factor that affects Jetty use in different aspects. The longer the distance, the less likely the users to shift from car trips. Also, the longer trip distance increases the odds of using a van over a bus. Lastly, the longer the user's average trip, the more likely the user to use Jetty more frequently, mainly because long trips by Jetty save more time when comparing with alternatives that combine PT and other modes to complete a trip. The main indication of trip distance impact on Jetty use is the service's convenience in trip time and cost-saving compared to other means of transport.

The modes used to access and egress Jetty and their travel distances impact the service use. The proximity of the access and egress locations to the trip's origin and destination increases the frequency of Jetty use. This point is directly related to the service planning, which should consider the actual demand and users' requests for pick-up and drop-off locations (Onésimo Flores Dewey, 2019). Percentage of morning trips performed by users increases the odds of shifting from car trips to Jetty, the odds of using van over the bus, and frequency of Jetty use . This finding is related to the city traffic pattern, where the morning peak is more severe than the evening peak hour. We hypothesize that this result is related to the fact that people value the saving in trip times in the mornings more than the evening due to the time constraints to reach workplaces at a particular time (Paleti et al., 2015).

The interaction between Jetty use and PT use is evident in our findings. The use of Jetty increases in locations where Metro trains have larger service headways. Also, the deteriorating condition of PT vehicles and frequent break downs impact PT travel time (Sheinbaum, 2018), and may push commuters to other modes such as Jetty; where the user-specified reasons of vehicle quality and travel time reliability increase Jetty use as per the estimated models. Also, the relation between Jetty use and private vehicle use is represented by people shifting from car trips to Jetty to avoid parking problems, and performing multi-tasking activities while traveling in a Jetty vehicle, such as working, reading for pleasure, sleeping or studying, which cannot be performed while driving a personal car. The trip cost significantly influences the use of Jetty in different aspects; fare increases the odds to shift from car trips to Jetty (mainly due to the savings in travel cost between the two options). Also, increased fare boosts the odds to choose bus over van (buses are almost 50% cheaper than vans, see Table 11), and fare reduces the frequency of Jetty use. Also, the deteriorated security situation in CDMX (Rivadeneyra et al., 2015; Mejía-Dorantes and Soto Villagrán) increase Jetty use; where people use van over the bus (the van is smaller in size, and for some people is perceived as more secure than traveling by bus). Finally, we found that a perceived larger security of Jetty against harassment increases the frequency of Jetty use.

6.2. Study limitations

This research represents a methodology for studying shared mobility services using different sources of information. The study has some limitations, which we believe did not impact the study's results and purpose. We believe that similar studies could learn from these limitations to avoid them. Firstly, regarding the survey design, the survey did not investigate the marital status and the number of children in the respondents' households. In some of the shared services studies, the number of children in the household has proven to be a significant factor impacting the use of the services (Chakrabarti and Joh, 2019; Dias et al., 2017). However, the primary purpose of using the service in question as indicated by the users is work trips (Tirachini et al., 2020), which is generally a solo trip (Lavieri and Bhat, 2019). Secondly, regarding the data collection process, the survey did not consider the people who did not use the service. Also, the survey was conducted online. In similar studies, face-to-face interviews are recommended to be used in combinations with an online survey to avoid the possibility of non-coverage bias (Alemi et al., 2018a). Also, the survey sample sociodemographics are not in line with the city average population sociodemographics in terms of having higher education, higher income levels, and higher car ownership rates. However, the sample coincides with the general characteristics of shared mobility services users as demonstrated in several studies in different countries, such as the UK, USA, Canada, Germany, and Australia (e.g. Degele et al., 2018; Howe and Bock, 2018; Kim et al., 2015; Shaheen and Martin, 2015; Murphy and Usher, 2015). The models' estimation did not consider the use of control functions or instrumental variables to check the possibility of endogeneity existence as it was outside the scope of this work. However, we plan to investigate such a possibility in future work, as the problem of endogeneity is not well studied in shared mobility research due to the service's novelty. The estimated models' and analysis' results should not be generalized for all the other pooled rides services with different operational schemes compared to the service used for this research case study. Mainly, if the other services do not consider fixed routes and schedules or at least one of them, and they pooled trips materialization might depend on the number of users using the service and the probability of matching with other users that might impact the service use and acceptance due to the traffic detouring and delays that might result from the matching process. Finally, the service information collected for this research, Jetty, is considered a new service with the beta version of the application launched in July 2017 (Onésimo Flores Dewey, 2019), and service is exponentially growing; therefore, the conclusion of this study would be due to the early adoption behavior and not for the regular use travel patterns; however, the study reveals insights to the use of pooled rides, which is not yet widely discussed for the absence of user-level data.

7. Conclusion, and recommendations

7.1. Conclusion

This paper investigated the factors impacting the shift from different modes to a pooled service, the use of the different pooled services vehicles size, and the frequency of use of a platform that organizes pooled rides, Jetty. The data used for the analysis and modeling were collected through an online survey deployed for the service users, and 1118 responses suitable for the analysis were received. The results underscore the value of users' sociodemographics, user travel pattern (attitudes), and trip and service characteristics on service adoption and use process. The econometric models that were estimated can be integrated into broader travel demand models to increase the quality of travel predictions by incorporating shared services into city-wide travel demand models. Also, the estimated models can be informative in terms of strategic planning as sociodemographic variables representing the population's demographics are included.

We find that the shared mobility platform under study represents a more convenient, reliable, and safe option for its users, than the travel alternatives that it replaces for commuting trips, mainly PT, private cars and ride-hailing or taxi. The platform extends the users' accessibility to the job centers that attracts Jetty trips in the morning period. Such organized service; therefore, serves as a tool to bridge a gap in travel demand. The actions required to increase or maintain the travel demand in sustainable modes, such as a changes in land use and PT network and infrastructure improvements, require significant long-term investment, which is not always easy to materialize. Pooled rides services represent a quick fix for extending the coverage of the PT network and the ever-growing demand, with a potential to reduce the VKT if planned, operated, and integrated correctly in the wider PT network and not as a local fix.

Notwithstanding, the results from our research also show some drawbacks triggered by the service, as the service is mostly used by middle- and high-income commuters given the job centers served and the level of the fare. This issue highlights the need to account for equity considerations in the future planning of platforms for shared rides and their more proper integration into the general public transport landscape. Therefore, lessons learned from Jetty could be summarized as (i) considering the actual demand and users' requests to dynamically locating and relocating pick-up and drop-off locations to minimize the access and egress travel time and distance and subsequently encourage the use of active mobility for the access and egress. (ii) Thoroughly consider the land use, sociodemographic, and job availability indexes when planning for new services. (iii) Including all the income groups and marginalized groups under the service coverage umbrella by investigating the factors behind the non-adoption.

7.2. Recommendations

Based on the findings, discussions, and scope of this research, we derived two sets of recommendations, the first set is regarding policies and practices to be adopted to increase pooled rides usage for their potential to reduce traffic externalities (Hou et al., 2020; Li et al., 2019; Shaheen and Cohen, 2019).

7.2.1. Policy recommendations

Dedicated municipal departments should be appointed to follow up, manage, and monitor the operations of shared mobility services, especially pooled rides, to ensure these services positively impact social welfare and their achievement of the targeted sustainability goals and mitigate any potential negative impacts. Pooled rides services should be integrated within the current and planned public transportation network to increase the transportation network coverage, encourage multimodality, and attract more users. The public–private partnership should be considered to increase the collaboration in many aspects, such as dedicating and prioritizing the right of way (parking areas) for pooled services, sharing the risks of new service financial loss to increase the operations resilience at the early operational stages (Cohen and Shaheen, 2018). Public authorities should incentivize the use of pooled rides, especially for users who are currently using low occupancy rate vehicles such as private passenger vehicles, taxis, and ride-sourcing to encourage the shift to pooled rides. In addition, authorities should encourage employers to facilitate, organize, and subsidize pooled rides for their employees. Moreover, pooled rides services, similar to other shared mobility services, attract users with high-income levels, and the service used depends on the ownership of a smartphone device and a credit card. These properties exclude low-income groups, the unbanked population, and the non-owners of smartphones; therefore, special facilities for those groups should be considered to enable their access to the shared mobility services in general, specifically for pooled rides. Also, authorities should consider subsidizing such services, especially in cases where public transportation does not have adequate Spatio-temporal coverage, to ensure the equity of use (Shaheen et al., 2020).

7.2.2. Future work recommendations

The second set of recommendations are regarding future work, including the coverage of non-users and the consideration of face-to-face interviews to avoid coverage bias. In this research, two latent attitudinal variables were used to investigate the impact of users' travel behavior on using pooled rides. Other attitudinal and latent behavioral factors such as evaluation of safety and security, the value of time, technology savviness, and adoption of other shared economy services could be included in the survey design to investigate the impact of those attitudes on adapting pooled rides. A stated preference survey investigating how users of pooled rides value their time compared to non-users will guide the operators and the authorities for a fair pricing scheme for such services. Finally, as the essence of using the pooled rides is to increase the occupancy of the vehicles relative to the standard use of private cars, research on how the current COVID-19 pandemic impacts and will impact travel behavior for an unknown time should be done as well, in particular, to understand the medium-term effects of the pandemic on the willingness to share rides with other people.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix. Additional analysis

See Tables A.14 and A.15.

Table A.14
GTFS files data summary statistics.

Distance to the nearest station in (Km)	Mean	SD	Min	Max
CDMX Bus	9.88	6.05	0.02	37.83
Subway	5.07	4.86	0.09	36.05
Metrobus	5.17	4.36	0.12	33.55
Light Rail	8.91	5.67	0.05	38.40
RTP	1.94	3.80	0.02	29.21
RTP-ESP	3.26	4.12	0.10	31.52
Suburban Train	13.02	6.74	0.48	32.12
Trolleybus	3.65	4.85	0.01	35.35
Headway at the nearest in (s)	**Mean**	**SD**	**Min**	**Max**
CDMX Bus	12	2	4	16
Subway	4	1	2	6
Metrobus	5	3	3	30
Light Rail	9	4	7	15
RTP	32	17	4	85
RTP-ESP	5	0	5	5
Suburban Train	10	0	10	10
Trolleybus	4	1	2	6

Table A.15
Shift to Jetty from car-based modes significant variables summary.

Variable	Car trips	No-Car trips
	Count (Pct.%)	Count (Pct.%)
Age		
46 or More	66 (10.91%)	77 (15.01%)
Between 18 and 25	87 (14.38%)	57 (11.11%)
Between 26 and 35	282 (46.61%)	244 (47.56%)
Between 36 and 45	165 (27.27%)	131 (25.54%)
Missing	5 (00.83%)	4 (00.78%)
Gender		
Female	311 (51.4%)	253 (49.32%)
Male	294 (48.6%)	260 (50.68%)
Household Size		
Between 1 and 2	189 (31.24%)	125 (24.37%)
Between 3 and 5	353 (58.35%)	317 (61.79%)
6 and More	38 (6.28%)	56 (10.92%)
Missing	25 (4.13%)	15 (2.92%)
Personal Income		
20K or less	218 (36.03%)	281 (54.78%)
20K–40K	214 (35.37%)	141 (27.49%)
40K or More	81 (13.39%)	25 (4.87%)
Missing	92 (15.21%)	66 (12.87%)
Driving License		
No	83 (13.72%)	138 (26.9%)
Yes	522 (86.28%)	375 (73.1%)
Number of Cars in the Household		
No cars	73 (12.07%)	137 (26.71%)
1	288 (47.6%)	232 (45.22%)
2 or more	244 (40.33%)	144 (28.07%)
Education		
Bachelor or higher	564 (93.22%)	442 (86.16%)
Other	38 (6.28%)	69 (13.45%)
Missing	3 (0.50%)	2 (0.39%)
Employment		
Employ_Full time	538 (88.93%)	465 (90.64%)
Employ_Other	67 (11.07%)	48 (9.36%)
In City Residents		
No	135 (22.31%)	90 (17.54%)
Yes	470 (77.69%)	423 (82.46%)
Activity Use of Smart phone		
No	150 (24.79%)	158 (30.8%)
Yes	455 (75.21%)	355 (69.2%)
Reason Fare		
No	345 (57.02%)	368 (71.73%)
Yes	260 (42.98%)	145 (28.27%)
Reason Avoid Parking Problems		
No	521 (86.12%)	469 (91.42%)
Yes	84 (13.88%)	44 (8.58%)
	Mean± (SD)	Mean± (SD)
Percent of Morning Trip %	54 ± (33.5)	45 ± (36)
Jetty trip Distance (km)	25.3 ± (6.88)	23.9 ± (6.77)
Number of modes replaced by Jetty	2.16 ± (0.71)	2.11 ± (0.92)

N = 1118.

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