



Analyzing User Behavior in Selection of Ride-Hailing Services for Urban Travel in Developing Countries

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Abstract

Recent developments in urban transportation services are rapidly transforming the way people make their trips. Around the world, the most controversial and rapidly growing mobility services in recent years are ride-hailing services (RHS) offered by transportation network companies (TNCs) such as Uber and Ola. This research estimates the demand for RHS vis-à-vis other modes and further expands to estimate usage propensity of RHS in the capital city of India, New Delhi. A discrete choice modeling framework is developed based on a household travel surveys ($N=426$) conducted in 2019. Two models were developed, a multinomial logit (MNL) model, to estimate the factors that lead to the adoption of RHS, and an ordered logit (OL) model, to estimate the frequency of usage of RHS. The results reveal a comprehensive set of socio-demographic and behavioral factors which leads to greater adoption of RHS. The variables such as household income, vehicle ownership, and use of smartphone are found to be important predictors (with a 95% significance level) of service adoption of RHS. The model results also suggest that RHS are likely to be used infrequently, and when it is being used, they are more likely to be used by the younger population and during the weekends. Overall, this research brings valuable and novel insights into the adoption and usage of RHS in India.

Keywords Ride-hailing services · Mode choice · Multinomial logistic regression · Ordered logistic regression · Public transport

Introduction

In the past decade, urban transportation systems around the globe have witnessed disruptive transformations, largely attributed to the continuous advancement in information and communication technologies (ICT). One of the most

popular, widely adopted rapidly evolving, and controversial products of such advancements are ride-hailing services (RHS) being provided by the transportation network companies (TNCs). RHS are quite different from traditional modes of travel, where passengers and drivers traveling to the same destination are paired using a mobile application. To get a sense of how popular their usage has rapidly increased the RHS are, Uber, the largest RHS provider in the world, completed 2 billion rides up until the first 6 months of 2016, but and then subsequently doubled the ridership within just the next 6 months [2]. In addition to Uber, which is already operating in more than 500 cities globally, there are other RHS providers that operate in different parts of the world, such as Lyft, Didi, and Ola. RHS are one of the fastest-growing sectors, which is evident from the Fortune's list of unicorns. Out of the top 25 companies in that list, 4 are engaged in providing such shared mobility services, with Uber topping the list, with a total valuation of US \$ 69 billion [3]. This certainly indicates an increasing public interest in such services. Needless to say, these services provide a higher level of comfort and convenience in terms

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of last-mile connectivity, flexible payment options, easy access, and luxury the opportunity of traveling by car, which are predominant reasons for their higher expeditious market penetration growth and public acceptance in many cities.

As far as Indian cities are concerned, the first Uber ride took place in August 2013 in the city of Bangalore [4]. During the year 2015–16, ridership of RHS in India grew almost 4 times, resulting in an estimated 70 million trips monthly. Given that ride-hailing services attract a significant number of commuters from different modes [5] and ever-increasing market penetration of such RHS, their overall impact within the Indian urban transport ecosystem needs to be studied [6]. In order to do so, this paper first presents the evolution and characteristics of RHS worldwide, followed by their acceptance and impacts they have had in the developed economies. This information is subsequently translated into devising the framework for estimating the factors that impact users' choice and the modal share of RHS in New Delhi, India.

This research is an attempt to find factors that influence the demand for RHS and their impact on other mode choice behavior in an urban area. More specifically, the objective is to determine the factors that drive the RHS use and subsequently model the demand for RHS. This research presents an empirical investigation on demand for RHS in the New Delhi area through the application of two logit models based on a household travel survey ($N=426$) conducted in 2019. The multinomial logit model estimates the demand for RHS as compared to other urban travel modes, including RHS, whereas the ordered logit model specifically estimates the demand for RHS in terms of its frequency of use. The results are then used to measure the impact of policy interventions on RHS ridership.

Literature Review

Evolution and Characteristics of RHS

The RHS have changed in character since their inception. Initially, RHS were conceptualized as ride-sharing services, where they primarily were matching the rides of users with that of a driver (owner), who was already traveling along the route, whereas in its current state, it is more like an app-based taxi service. Hence, often the word ride-sharing is misused when referring to ride-hailing companies in their original form [1].

The remarkable milestone that changed the face of the RHS market happened over a decade ago, when UberCab (now Uber) was launched in 2009 in San Francisco. Initially, it was launched as a luxury car service, but soon it expanded by offering a range of car services, while other similar players joined the market. Uber is estimated to have 110 million users worldwide and operational in 785

metropolitan areas worldwide as of 2019.¹ Besides, there are many other RHS providers around the world like Uber, such as Lyft (in USA), DiDi (in China), Ola (in India), Grab (in Singapore), and Careem (in Dubai). In the transport sector, RHS providers are among the most profitable firms [2]. The world's top four RHS providers—DiDi, Uber, Lyft, and Grab—have a combined valuation of \$166 billion, according to the Boston Consulting Group (BCG). It should be noted that these RHS have achieved this remarkable growth without owning a single car in their offered fleet and hiring a single driver as their employee [3]. The huge success of RHS can be largely attributed to their ability to take advantage of the widespread adoption of smartphones, internet usage, and GPS technologies while offering a comfortable and convenient mobility service [2].

In a very short period, RHS have gained in popularity and have managed to capture a segment of the urban transport market share and is competing with other modes of urban transportation. However, acceptance of these services in different cities across the globe has not been the same. The popularity, acceptance, and even the name of these services varies by country. Although the same RHS provider may operate in multiple countries with the same name, they might offer a different level and range of services. The scenario of RHS is completely different in the case of developing countries. In the developing world, the RHS managed to survive and grow rapidly. For example, in Indian cities, the first RHS was started by Uber. After their launch in 2013 in the city of Bangalore, the RHS market grew dramatically in other parts of the country, especially in metropolitan cities with new operators like Ola entering the sector [4]. The arrival and reception of RHS (especially Uber) in the global north (United States, Germany, and Sweden) have been ridden with conflicts which arise mostly from regulatory flashpoints provoked by Uber and other coalitions (for example, New York City Taxi and Limousine Commission). [5]. Specifically, in the Indian context, prior to 2019, the Motor Vehicles Act of 1988 did not address ride-hailing services. Even the Motor Vehicles (Amendment) Bill, 2019 defined ride-hailing services only as digital intermediaries and assigns the responsibility on the states to issue licenses and develop policy guidelines, which are evolving slowly. Hence, there is substantial ground to believe that RHS gained from such policy loopholes (e.g., no-bar surge-pricing and driver refusal) to attain an unjustified superiority over comparable travel alternatives (e.g., city taxi services) [6].

¹ <https://www.uber.com/global/en/cities/>.

RHS and Travel Mode Choice

The mode choice of any individual is influenced predominantly by three sets of factors, namely individual characteristics, trip characteristics, and the level of service provided by the transport infrastructure/service [7, 8]. In addition, various qualitative factors, such as perceived safety and security [9], comfort and convenience, and ability to multi-task during the trip, are also considered to be significantly influential in terms of mode choice [10]. There are abundant studies on mode choice behavior, however, research of mode choice in the context of RHS is in its infancy because of only a decade of their operations around the world, and also lack of publicly available data [11].

To understand how RHS are affecting the travel behavior and urban transport ecosystem, one needs to understand the factors that drive users to avail or avoid RHS. In this regard, a comprehensive review of the existing literature from the developed world was carried out [7, 11–20]. In these studies, several attributes, both objective and subjective, along with socio-demographic factors were identified and evaluated in terms of their implication on RHS users' travel behavior. Alemi et al. [21] report that the choice of RHS is influenced by household income, education level, non-work-based trip characteristics, accessibility of public transport, and dependency on taxi /IPTs services. Another study found that factors such as fare, parking, comfort, convenience, safety, availability, reliability, and weather are the main influencing factors for RHS use [22]. Furthermore, the study also revealed that a large number of RHS users would go back to using transit if RHS are not available. Research also suggests that RHS predominantly attract their passengers from both taxis and public transport equally [18]. The study by Habib [11] found that taxis are the main competitors of RHS. Various other studies have reported that the younger population is more likely to avail of RHS as opposed to the elderly [2, 14]. In addition, these studies also point out that higher income groups and individuals with higher education are also more likely to use RHS. The primary reasons for the younger population to use RHS more than the elderly are the higher likelihood of adoption of technology-based services and the lower ownership of cars [23]. In terms of the spatial distribution of RHS trips, a study [24] found that the RHS trips among proximally located zones are spatially dependent. Furthermore, during the weekdays, RHS compete with transit services. A recent study by Devaraj et al. (2020) highlights the interrelationship between the three choice dimensions of consideration of intermediate public transport (IPT), adoption of RHS and the subsequent usage intensity of RHS in the Indian context [25]. The study observes significant endogeneity between consideration of IPT and adoption of RHS. Table 1 summarizes the methodologies and findings from selected studies conducted in different

regions to clearly understand the mode choice behavior of RHS users. This set of rich literature gives a roadmap to undertake similar research in the case of Indian cities.

Impact of RHS

In a very short period, RHS have had a significant impact on travel behavior and hence mode share [26]. Some authors have advocated the positive impacts of RHS on urban transport systems. For example, Stiglic et al. [27] suggest that integration of RHS and public transport could be beneficial in terms of last-mile connectivity to and from transit stations. Similarly, a study by Murphy and Feigon (2016) found that the RHS complement public transport services and overall improve the urban transport system. Additionally, Yu et al. [28] claimed that RHS might reduce car ownership and benefit the environment.

Alternatively, the biggest concern of researchers working in this field is that the RHS might compete with transit services and cause a greater number of cars on the road and hence worsen the congestion and emissions. It has been argued by Erhardt et al. [29] that ride-hailing services attract a significant proportion of transit and active mode users, because of the comfort and convenience that it has to offer as compared to these modes of transport. According to CityLab report, RHS add up to a significant number of empty kilometers (also known as *deadheading*) to pick up the next passenger. This eventually leads to an average passenger occupancy of below one, and as such may lead to a scenario that further contributes to urban congestion.

Growing research in this field is showing that RHS may not change user's personal attitude when it comes to the desire of owning a car [14]. RHS might lead to a greater number of cars on the road while reducing public transit ridership [30], as they are attracting passengers from public transport [14, 31] and not so efficient integration with public transport [8]. In another study by Tirachini and Rio [20], the findings were similar in the city of Santiago de Chile, where RHS caused around 11% reduction in the ridership of public transport and thus, significantly worsening the congestion level. These studies are aligned with that of Henao and Marshall (2018), which suggests that RHS are successfully competing and substituting more sustainable modes like public transport and active modes. Needless to say, the findings from these studies certainly question the overall sustainability of the urban transport system in the presence of RHS [32].

It can be said that the introduction of RHS has transformed the urban transport ecosystem and added a new dimension to it. However, the results in the literature are not consistent enough to draw any conclusion. It could be said that the impact of RHS on travel behavior is predominantly driven by the level of availability of transit services, study

Table 1 Representative research on RHS' mode choice

Author(s)	Area	Objective(s)	Methodology	Key findings
Rayle et al. (2016)	San Francisco	To find how RHS impact the use of public transit and overall vehicle travel	Based on the comparative analysis of matched taxi and public transit data using intercept survey data from RHS hotspots	In absence of RHS: 33% would use public transit, 39% would use a taxi, 10% would use NMTs, 6% use their car
Alemi et al. (2019)	California	To identify influencing factors for RHS usage	Assessment of a latent-class adoption model that captures the heterogeneity in the tastes/preferences	RHS choice is influenced by household income, education, accessibility of transit stops
Habib (2019)	Greater Toronto and Hamilton	To investigate what drives the use of RHS	Estimation of Semi Compensatory Independent Availability Logit model	No significant competition between RHS and other modes
Lavieri et al. (2018)	Texas	To analyze the impact of RHS on individual travel	Estimation of a fractional split model and a Spatially lagged multivariate count model	RHS trips are spatially dependent and also the weekend and weekday trips are correlated
Clewlow and Mishra (2017)	USA	To explore the adoption, utilization, and early impacts on travel behavior of RHS	Based on collection of a large, representative sample of survey respondents in seven major metropolitan areas	21% of adults personally use RHS; RHS users have higher personal vehicle ownership rates than only transit users
Mahmoudifard et al. (2017)	Chicago	To analyze the characteristics, preferences, and behavior of the RHS users	Developing an NL model based on the preference of riders in absence of RHS based on survey data	In the absence of RHS: 55–60% of RHS users would use public transit
Devaraj et al. (2020)	Chennai	To find the endogeneity between consideration of IPT and adoption of RHS	Developing a tri-variate joint model	Interrelationship between the three choice dimensions of consideration of IPT, adoption of RHS and the subsequent usage intensity of RHS in the Indian context
Present study	New Delhi, India	To determine the factors that drive the RHS use and subsequently model the mode share and ride frequency of RHS	Application of two logit models (multinomial logit and ordered logit) based on a household RP travel survey	Younger generation and women are more likely to use RHS RHS are predominantly used for non-work-based trips RHS are predominantly drawing their frequent passengers from public transit

area characteristics, and socio-demographic attributes. Furthermore, how RHS will affect the existing urban transportation system is also guided by the existing policy and regulatory framework present in the study area. This research attempts to fill the gaps in two ways: (1) estimate factors that impact current modal share of motorized modes vis-à-vis RHS; (2) estimate the factors that impact the frequency of choosing RHS to assess the heterogeneity in usage pattern. The study brings valuable and new insights in understanding the changes in urban travel demand areas as a result of the entry of RHS in developing economies that characteristically have different transport infrastructure when compared to developed countries.

Data Collection and Exploratory Analysis

Study Area

The primary data used in the present study have been collected through surveys administered in the capital city of India, i.e., New Delhi. It is worth mentioning that currently New Delhi is one of the largest metropolitan cities with an estimated population of 19 million (Census, 2011). Furthermore, the heterogeneity available in terms travel choices makes it an ideal case for carrying out the study. Also, it has one of the largest public transport systems in the country, consisting of a mass rapid transit system (Metro Rail) as well as comprehensive city bus system. Like other metropolitan cities around the world, New Delhi has also witnessed a significant increase in the ownership of personal vehicles. As far as RHS in New Delhi is concerned, Uber ranks the Delhi NCR region among its top 10 markets globally based on the number of trips taken, making it the only Indian city in the top 10, highlighting its strategic importance in Uber's global portfolio, with residents taking more than 1 million rides each week (PTI, 2017). New Delhi also saw the highest number of UberPOOL trips in comparison to other metro cities in India. As per the Boston Consulting Group (BCG) report in terms of the number of cities served, India is the second-largest market for Uber, after USA. Besides, New Delhi is dominated not only by Uber but also by similar ride-hailing companies such as Ola. Uber claimed that they have emerged as the most preferred mode of commuting, when compares to other similar service providers, after the resumption of travel activities post COVID-19 lockdowns, followed closely by low-cost products such as Auto and Moto [1]. Over the years, there has been a huge increase in the number of cars and two-wheelers, while, on the other hand, public transport trips and its modal share have declined considerably. As such, the impact RHS has had on the mode choice and travel behavior is of interest to this study. Considering the market share of RHS in New Delhi, availability or range of public

transport and intermediate public transport, coupled with a large number of personal vehicles (cars and two-wheelers) on roads, makes it an ideal Indian city to study the changes in travel behavior under the influence of RHS.

Data Collection

First, a comprehensive set of factors related to RHS adoption, including socio-demographics (e.g., income, age, and gender), trip features (e.g., travel time and trip purpose), and RHS service attributes (e.g., comfort and reliability), were identified from the available literature. In the present study, no distinction was made among different RHS service types,² i.e., shared vs. solo RHS rides, sedan/SUV vs. 2-wheeler vs. auto-rickshaw RHS modes, or Uber vs. Ola RHS services providers. The factors were used to carry out a revealed preference (RP) household survey via computer aided personal interviews using mobile tablets. The mode of the survey was face-to-face interview while recording the responses using internet-based Google forms to reduce minimize human errors as well as data entry burden.

The mathematical formulation that was used for calculating sample size for a given population (approximately 4.5 million in our case) (Krejcie & Morgan, 1970) is mentioned as follows:

$$S = \frac{\chi^2 * N * P * (1 - P)}{d^2 * (N - 1) + \chi^2 * P * (1 - P)} \quad (1)$$

where N is the population size, P is the population proportion (assumed 0.5 for maximum sample size), and d is the degree of accuracy expressed as a proportion (assumed 0.05).

Moreover, Chi-square value needed to be calculated for the degree of freedom 1 for a requisite statistical confidence level.

According to this expression, the minimum sample requirement for any city with more than 10 lakh population is about 384. Finally, a total of 600 individuals, 1 from each household, randomly distributed among the 9 districts of New Delhi, were interviewed. Subsequently, the database was screened to eliminate the inaccurate entries, partially and un-filled responses. At the end, 426 datapoints were used in the model estimation purpose. The entire survey questionnaire was grouped into four major sections—(a) household-related information, (b) trip information, (c) information related to the use of RHS, and (d) individual characteristics. The authors would also like to acknowledge the fact that there has been an expected over-representation of the educated group in the collected sample as they were

² Please refer to <https://www.uber.com/us/en/ride/ride-options/various> for various ride-hailing service options.

Table 2 Sample characteristics of socio-demographic variable

Independent variables: <i>categorical variables</i>	Sub-categories	Sample distribution ^a (%)	Census distribution ^{a,b} (%)
Gender	Male	64.0	51.5
	Female	36.0	48.5
Age	Youth (18–30 years)	39.2	41.0
	Middle age (30–50 years)	49.7	41.0
	Old age (older than 50 years)	11.1	19.0
Education	Class X or lower	19.7	52.6
	Class XII	26.4	18.1
	Graduate or above	53.9	29.3
Household income ^c (INR) (monthly)	Low-income HH (0–75 K)	65.6	82.7
	Middle-income HH (> 75–150 K)	24.0	12.5
	High-income HH (more than 150 K)	10.4	4.8

^aThe percentages are rounded off to one decimal places.

^bSource: 2011 Census data India.

^cThe distribution for income represents urban population only. Source: IHDS, 2011. “India Human Development Survey [Online].” Available: ihds.umd.edu [Accessed]

relatively more open to be surveyed (see Table 2). Hence, the results could only be generalized with words of caution.

The mode share has also been analyzed to obtain a better idea about the traveler preference for various urban travel alternatives (see Fig. 1(a), (b)). At the same time, the mode share has also been analyzed separately for the weekday and the weekend trips to assess the heterogeneity in mode choice pattern. It can be observed that motorized weekday trips mainly comprise motorbike (23.10%), IPT (12.10%), and car (8.70%) whereas weekend trips had relatively greater share of car trips (15.8%) as compared to IPT (11.1%). Besides, the share of public transit also goes down in weekend trips (14%) as compared to weekday trips (10.90%). Most importantly, the share of RHS is minimal for weekday (0.90%) but considerable for weekend trips (10.10%).

Methodology

This study used two econometric choice models to derive the results. This research identifies factors that influence the preferences for RHS vis-à-vis other modes and further expands to estimate usage propensity of RHS in New Delhi. The first model, i.e., multinomial logit (MNL) model aids in understanding the (discrete) choice of ride-hailing vis-à-vis other urban travel alternatives but it does not differentiate between higher and lower usage of RHS. This is why we empirically estimate the second model, i.e., ordered logit (OL) model to obtain insights about factors influencing higher (or lower) utilization of RHS. Lastly, the models were used to carry out sensitivity and scenario analysis, to estimate the likely effect they would have on RHS usage.

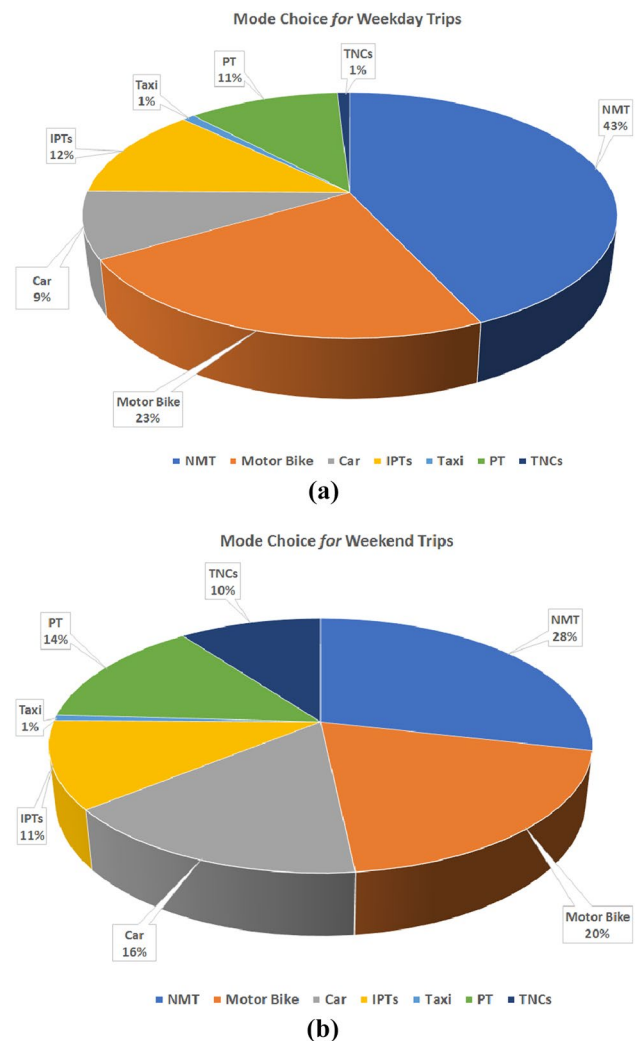


Fig. 1 a Mode share for weekday trips, b Mode share for weekend trips

Table 3 Independent variable description

Variable name	Description	Categories
Household level variables		
Household size	Number of individuals living in the household Number of cars owned by the household	HH size 1, 2, 3, 4, 5+
Vehicle ownership	Combined monthly income from all members of the household	No. of cars—0, 1, 2, 3+
Household income		Low, middle, and high income
Personal level variables		
Age	Age of the surveyed individual at the time of survey.	18–21, 21–30, 31–40, 41–55, 55–65, 65+
Educational level	Level of education at the time of the survey	Class X or lower, up to class XII, graduate
Tech savviness	Frequency of use of smartphone for trip planning purposes	Smartphone use out of 5 trips—1, 2, 3, 4, 5
Trip-specific variables		
Trip day	Day on which the trip was made by the individual	Weekday and weekend trips
Trip purpose	Purpose for which the trip was made by the individual	Work-based and non-work-based trips
Alternative specific variables		
Travel time	Time taken to make the trip by the chosen mode	Absolute values in minutes

Estimation Results of MNL Model

Table 3 presents the results of mode choice model (MNL), which was estimated using the software package ‘*mlogit*’ in R. The modes considered are motorcycle, car, public transport, intermediate public transport, and RHS. Intermediate Public Transport (IPT), also known as Paratransit, refers to vehicles (such as auto-rickshaw, which is common in India) used on-hire for flexible passenger transportation, that do not follow a fixed time schedule and may or may not follow a fixed route, offered by usually a private independent operator. In the Indian scenario, paratransit modes are very popular means of travel for short distance trips. Table 3 presents the description of independent variables used in the model development.

In the process of building a reasonably working model, different variable combinations were tested one by one iteratively. Overall, the signs and coefficient estimates are consistent with a-priori expectations. The alternative specific constants (ASC) for the modes indicate the relative preference for the modes when all else is equal. The values presented in Table 4 suggest that the ASCs of all modes except intermediate public transport (IPT) is lower than motorcycle (base).

Notably, the variables tech savviness for public transport, trip day for car, and trip purpose for car are not significant at 90% confidence interval, but has been considered in the final model. The signs and coefficients of even the non-significant (in 90% confidence interval) variables are intuitive and reinforces the insights provided by the present model. Besides, considering the limited sample size of the current study, we have decided to include such variables which are close to 90% significance level and aids in model interpretation. In fact, such variables also improve the model

goodness-of-fit (McFadden R2) which rather supports instead of contradicting their inclusion.

The model suggests that when it comes to choosing RHS, larger household sizes are much more likely to use it relative to other modes, probably because it becomes more convenient and cost-effective when trips are combined with other members of the household. However, households with higher income levels are observed to have lower propensity to choosing RHS, which might be attributed to their strong preference of using personal vehicles. A more direct effect could be found wherein higher vehicle ownership is associated with lower propensity of choosing RHS. Results indicate that the younger generation is more likely to adopt RHS, pointing to the likelihood that they may have higher access to, or familiarity with, the world of smartphone apps and internet use, considering that these are app-based services. This is also reinforced with the observation that higher propensity of RHS adoption is positively correlated with higher education qualifications. Also, the younger generation is more likely to be flexible with their travel decisions and tend to try out new things in every aspect of life. It should also be noted that RHS can be cost-effective when shared, which makes it attractive for the young generation to travel along with their friends sharing the total fare while enjoying the comfort of a car. In terms of the use of a smartphone, it was found that individuals with a higher frequency of smartphone use for trip planning purposes are more likely to select RHS, which is intuitive considering the nature of these services. Furthermore, one of the most important findings from the model is that RHS are likely to be predominantly used for non-work-related trips, which are made largely on weekends, i.e., leisure trips. Moreover, this could also be attributed to the concerns associated with parking space/cost especially in and around popular leisure

Table 4 Estimation results of the multinomial logit model ($N=426$)

Coefficients	Estimate	<i>t</i> stat	Significance
Alternative specific constants			
Car	- 1.29	- 1.50	
Intermediate public transport	2.90	3.62	***
Public transport	- 2.27	- 2.73	**
Ride-hailing services	- 1.46	- 1.37	
Household level variables			
Household size			
Intermediate public transport	0.32	2.62	**
Ride-hailing services	0.54	3.91	***
Vehicle ownership			
Car	0.42	2.17	*
Public transport	- 0.38	- 2.33	*
Ride-hailing services	- 0.43	- 2.02	*
Household income			
Car	1.20	4.41	***
Intermediate public transport	- 0.72	- 2.69	**
Public transport	- 0.62	- 2.43	*
Ride-hailing services	- 0.96	- 2.96	**
Personal level variables			
Age			
Car	0.16	1.67	
Public transport	- 0.41	- 4.31	***
Ride-hailing services	-0.33	-2.78	**
Educational level			
Car	0.50	3.12	**
Intermediate public transport	0.84	4.96	***
Public transport	0.90	5.49	***
Ride-hailing services	0.69	3.19	**
Tech savviness (smart phone use)			
Intermediate public transport	0.17	1.86	
Public transport	0.10	1.23	
Ride-hailing services	0.20	1.70	
Trip-specific variables			
Trip day (weekend/weekday)			
Weekend dummy for car	1.24	4.55	***
Weekend dummy for Intermediate public transport			
Weekend dummy for public transport	0.96	3.67	***
Weekend dummy for ride-hailing services	2.49	7.04	***
Trip purpose (commute/non-commute)			
Commute trip dummy for Car	- 0.10	- 1.42	***
Commute trip dummy for intermediate public transport	- 0.42	- 5.73	***
Commute trip dummy for public transport			
Commute trip dummy for ride-hailing services	- 0.24	- 3.54	***
	- 0.66	- 7.68	***
Alternative specific variables			
Travel time			
Travel time for car	- 0.07	- 10.44	***
Travel time for public transport	- 0.07	- 11.09	***
Travel time for ride-hailing services	- 0.08	- 10.96	***

Weekend dummy corresponds to trips made on weekends (Saturday and Sunday)

Commute trip dummy includes all the trips to educational institutions and work places

(***) 99.9% significance, (**) 99% significance, (*) 95% significance, (.) 90% significance level.

Table 5 Estimation results of ordered logit model ($N=426$)

Coefficients	Estimate	<i>t</i> stat	Significance
Frequency of using RHS			
Never use (Base)			
Use monthly	- 2.71	- 3.61	***
Use weekly	- 5.37	- 6.84	***
Use regularly	- 8.07	- 9.32	***
Vehicle ownership	- 1.29	- 9.37	***
Household income	0.81	4.32	***
Gender (male—0/female—1)	0.34	1.46	
Smartphone user (yes—1/no—0)	2.01	3.08	**
Use of smartphone for trip planning (yes—1/no—0)	0.54	6.15	***
Trip purpose (work based—0/non-work based—1)	1.35	2.56	*
Preference in absence of RHS (PT—1/other—0)	1.46	4.69	***

(***) 99.9% significance, (**) 99% significance, (*) 95% significance.

destinations, viz., malls, movie theaters, restaurants, etc., which may be located in the central business district.

It is worth mentioning that a *choice-set partitioning test* (proposed by McFadden et al. (1981)) was conducted to compare the results from the full MNL model estimated with all outcomes (i.e., choices) to the results from a restricted estimation that includes only some of the outcomes [33]. At the end, IIA property holds for the present study, as the estimated coefficients of the full model are statistically similar (based on likelihood ratio test) to those of the restricted one. The Mcfadden R^2 value (0.25) indicates that independent variables explain about 25% of the differences in the explained variables. Since the value lies between 0.2 and 0.4, it indicates a good model fit [34]. In other words, the final model presented above is based on the combination of explanatory variables that best fit the choice behavior of the individuals.

Calibration attempts were made through re-estimating the model with the same set of variables as the original model, with only 70% of the original dataset. The re-estimation was performed 10 times to minimize biases, and the survey records (70%) were chosen randomly for each of the 10 attempts. The results showed that the mean value is not significantly different and the values are very close to the original model in each attempt. Furthermore, a validation attempt was made by comparing the probabilities of choice of the predicted mode with the probabilities of choice of the observed mode. The findings indicate that the expected versus observed model shares correlate strongly (McFadden R^2 value 0.6–0.7) with the RHS, PT, and car; and correlate moderately (McFadden R^2 value 0.4–0.5) with the motorcycle and IPT modes, suggesting that the model has reasonable predictive power.

Ordered Logit Model

The ordered logit model (see Table 5) is using the ‘ols’ function of the ‘rms’ (Regression Modeling Strategies) package in R-Studio (Harrell, 2022). Different variable combinations were evaluated iteratively, one by one, in the process of creating a final workable and rational model.

The frequency-specific constants shown in the results (threshold values) capture the effects of the unrecognized variables and errors in measurement. The level of frequent or routine usage of RHS (regularly use RHS) takes the smallest constant because it is the least represented in the dataset, and maybe the model did not capture its attributes well. All constants are negative and the frequency-specific constant for ‘never use RHS’ is zero, which indicates that, without comparing any other characteristics, ‘never use RHS’ is most likely to occur. This is expected as (never use RHS) is by far the most dominant response in the dataset.

The model suggests that when it comes to RHS adoption in terms of its frequency of use, it was found that individuals with vehicle ownership (car or motorcycle or both) are less likely to use RHS frequently because they might prefer to use their personal vehicles. Intuitively, frequent ride-hailing users are associated with comparatively higher household income because RHS is comparatively expensive, and

Table 6 Goodness of fit indicators of the multinomial logit model

	Constant only (coefficients = 0)	No constant (constant = 0)	Full model
Log-likelihood value	- 1240.70	- 951.30	- 835.98
McFadden R^2			0.252
Likelihood ratio index (Chi-square)			0.326 (609.36)

Table 7 Goodness of fit indicators of the ordered logit model

	Constant only (coefficients = 0)	No constant (constant = 0)	Full model
Log-likelihood value	167.68	201.46	227.92
McFadden R^2			0.464
Likelihood ratio index (Chi-square)			0.374 (585.46)

Table 8 Developed scenarios for multinomial logit model

Scenarios	% Change		
	Vehicle ownership	Travel time—car	Travel time—PT car
Base scenario	0%	0%	0%
Scenario—1	0%	+ 20%	– 10%
Scenario—2	– 10%	+ 10%	– 20%
Scenario—3	– 10%	0%	– 10%
Scenario—4	– 10%	+ 20%	0%
Scenario—5	0%	+ 10%	0%
Scenario—6	– 20%	0%	0%
Scenario—7	0%	0%	– 20%
Scenario—8	– 20%	+ 10%	– 10%
Scenario—9	– 20%	20%	– 20%

individuals with lower income might not be able to afford to use it on a more frequent basis. This is also observed in different studies globally [21] [35], where individuals with higher incomes are more likely to travel frequently by RHS, because they look for more comfortable and convenient options and they are willing to pay extra for it. Expectedly, individuals with a higher frequency of smartphone use for trip planning purposes are more frequent users of RHS. The model also suggests that RHS are predominantly drawing their frequent passengers from public transit as respondents showed their preference for the latter in absence of RHS. Similar to the multinomial logit model, the ordered logit model also suggests that frequent RHS trips are made for predominantly non-work/school-related trip purposes. Notably, the variable gender is not significant (albeit close to 90% CI) but has been considered in the final model because it helps in understanding higher usage of RHS by female respondents relative to their male counterparts. This is perhaps due to safety and security concerns in other modes.

The McFadden R^2 value of 0.464 indicates that independent variables explain about 46% of the differences in the explained variables. Since the value is close to 0.5, it indicates a fairly good model fit [34]. Similar to the MNL model, the ordered logit model was re-estimated with a randomly selected subset of 70% of the full dataset ten

times. In each validation iteration, the probabilities were calculated and matched with the observed value for each of the frequency category. Besides, it was repeated for ten times to avoid any biasedness in selecting sub-sample, i.e., 70% of the full sample. The result suggests that the mean value is not significantly different and the values are very close to the original model in each attempt. Furthermore, the predicted versus observed frequency usage of RHS correlates strongly (McFadden R^2 value 0.5–0.7) for each of the outcomes. The performance of the model has been assessed against two types of the goodness-of-fit indicators (Log-likelihood ratio index and McFadden R^2) (see Table 6–7). It is worth mentioning that the model has been observed to be at-par with the acceptable thresholds for both of these indices.

Scenario Analysis

The three variables ‘vehicle ownership’, ‘car travel time’, and ‘public transport travel time’ are considered to build different scenarios. The reason why these variables are taken into account is because of their impact on travel behavior (as discussed in Sect. 5.1). In addition, these three variables are also well suited to build different scenarios because these variables can be practically changed through certain policies/regulations. Such policy/regulation is already practiced by many of the countries to move towards a more sustainable transport system.

The different scenarios presented in the following table (see Table 8) are combinations of the three variables. To make different combinations of the variables, JMP software was used by making a D-optimal design. For that purpose, the allowed limit of change was kept to $\pm 20\%$. Therefore, the defined level of change for all the three variables was $\pm 0\%$, $\pm 10\%$, and $\pm 20\%$. The maximum limit was set to $\pm 20\%$ to keep the scenarios realistic, practical, and achievable. It can also be justified based on the sensitivity and elasticity. It was observed that no significant change happens in the modal share even after changing the attributes by $\pm 20\%$. The base scenario is the existing scenario without any intervention, or with a 0% change of the variables.

For each of the scenarios presented in Table 8, the results are predicted using the final MNL model estimates. To do that, for each of the nine scenarios, a change in the variables considered under that particular scenario was made to the survey dataset. For example, in case of scenario 6, both vehicle ownership and travel time in public transit in the dataset were reduced (less impedance) by 20% whereas the travel time by car was increased by 20% (more impedance). Finally, based on the MNL model developed, mode share was predicted using the final MNL model estimates. The Sankey diagrams presented below (see Fig. 2) present the predicted changes in mode share for best (scenario—9) and worst (scenario—6) scenarios using the final MNL model.

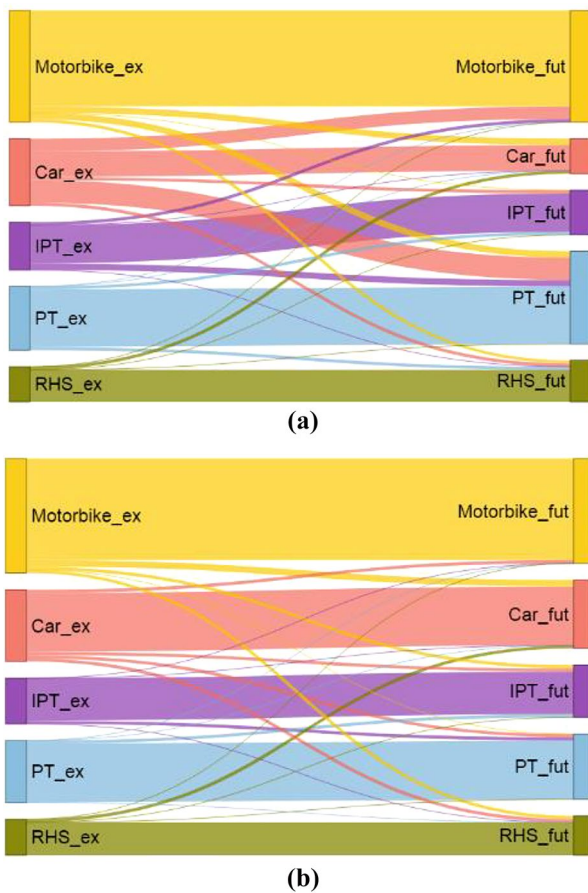


Fig. 2 a Sankey diagram for scenario—9, b Sankey diagram for scenario—6

The scenario—9 would translate into 11.7% decrease in car usage and 10.2% increase in public transport usage, which are highest among all the scenarios, whereas the scenario—6 is the worst with almost negligible changes in all modes albeit in sustainable direction, i.e., 0.6% decrease in car modal share and 0.5% increase in public transport share. However, even in the best scenario, the change in share of RHS is minimal (0.1%). The scenario analysis allowed us bring out such nuances. This indicates that even a 20% reduction in car ownership, combined with a 20% rise in travel time by car (indicating higher levels of congestion) and 20% reduction in travel time by bus (via dedicated lanes, bus priority signals, etc.), is not likely to increase the modal share of RHS. As such, there may be a need to bring structural changes in RHS operations, if they were to seek a larger mode share in New Delhi.

Conclusions and Future Research

Over the last decade, RHS offered by TNCs have grown rapidly around the world. The high growth and expansion

of such services worldwide, coupled with conflicting claims about their positive and negative impacts on the urban transport ecosystem, and very limited availability of their travel data, calls for a deeper investigation, particularly in developing countries. It is evident that socio-demographic factors play a very significant role in individuals’ mode preference behavior, and it is no different in the case of RHS. It was found that younger age groups are more likely to adopt RHS as compared to the older generation, probably because of their income strata, inability to buy a car, and familiarity with smartphone services. Furthermore, the individuals with lower household income are more likely to choose RHS as they cannot afford to purchase a private vehicle, so RHS satisfies their need to travel in a car, without buying one. However, owing to higher travel costs as compared to public transportation, individuals with lower household income are not the most frequent users of RHS. Interestingly, women are likely to be more frequent users of RHS mainly because using transit or IPT might not be perceived as safe mode of travel, particularly at night. As expected, it was found that RHS are more likely to be used by individuals who use smartphones for trip planning purposes, and they are also the most frequent users. One of the most adverse impacts that RHS is seemingly creating is deriving their customers primarily from public transit and more sustainable modes as discussed in ordered logit model results.

Overall, this research brings valuable insights into how various household and personal characteristics, along with trip specific variables, shape people’s travel behavior in an urban setting. This can be extended in the future to include various stated preference experiments to build further confidence into the results. Besides, one major caveat of the present study is that the choice of modes and the extent of usage of modes are modeled separately. As a result, there might arise endogeneity issues and/or biased parameter estimates due to common unobserved factors that influence both the mode choice as well as the extent of its usage. Future studies can use a joint MNL-Ordered logit framework or a unified MNL framework as used recently by [36]. Moreover, further studies might look into an understanding of travel behavior to explore impacts of other factors such as attitudes (behavioral factors) and built environment on commuters’ preference for RHS. Research should also be carried out to estimate the demand for various types of RHS, such as two-wheeler-based RHS, auto-rickshaw-based RHS, and bicycle sharing. If planned properly, the RHS can act as a feeder service to complement public transport. RHS can be effectively used to create a sustainable transport environment if it bucks the present trend and plays a supportive role to other green transport modes.

Recommendations

RHS has been observed to compete with sustainable modes of transport like public transport whereas it ostensibly fails its said purpose of drawing people out of their personal vehicles. Interestingly though, certain traits, as shown by RHS users, coupled with scenario analysis results, could be exploited to make the policy recommendations. Those are as following:

- (1) RHS users, predominantly from bigger households, exhibit their willingness (refer to Table 4) to choose RHS, which could be further promoted through various incentives (*for pooled/ shared rides*) by the service providers. As a large share of Indian households live in “extended families” [37] [38], i.e., one or more parents or relatives living under one roof, this demography may assist in the promotion and growth of RHS in urban areas.
- (2) Youth, between the ages of 18–30, who are the most likely users of RHS (refer to Table 4), could be further incentivized to adopt RHS. As India boasts of having nearly 47% of its population below the age of 25, this socio-economic group could be attracted to the various types of inexpensive ride-hailing or ride-sharing services [39]. A frequent user program could be devised to provide discounts to students traveling together on a daily basis to their schools/colleges.
- (3) It has been observed that tech savviness (refer to Table 4) plays a significant role in both choosing and frequently using RHS. The growing smartphone penetration in India, which is currently over 66%, and expected to reach 90% by 2032, is also likely to support the widening base of RHS across India [40]. As such, the RHS apps could be integrated with various public transit apps so provide a seamless travel experience where RHS acts as a feeder to major line-haul.
- (4) The scenario analysis results (refer to scenario 9; refer to Table 8) show RHS ridership may be enhanced by integrated strategies that restrict ownership and usage of personal vehicles, by various measures like fixing a ceiling for yearly car registration, congestion pricing, etc.; and prioritizing public transit, by measures such as priority transit lanes and extra green time at intersections. One such strategy was adopted by the operators of Uber and Ola in New Delhi during the days when the “Odd–Even” policy was implemented, where they scrapped surge-pricing to attract more users [41]. This policy has been formulated by the Delhi government to reduce the number of personal vehicles plying on the streets during the days of poor air quality. Singapore has also adopted a policy to limit the number

of private car registrations in order to reduce congestion [42].

- (5) The present study observes that RHS is mostly used by individuals with higher income (refer to Table 5). As such, other types of RHS, such as 2-wheelers, intermediate public transport (*e.g., auto-rickshaw and e-rickshaw*) should be further promoted so as to improve the affordability of RHS for larger sections of society. Rapido is an example of 2-wheeler RHS, which operates in several cities in India. Auto-rickshaw-based RHS, namely COOP and Tukxi, have been recently launched in the cities of Pune and Kochi, respectively [43]. Such types of RHS are likely to reduce the trip price and attract greater number of users.

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Declarations

Conflict of Interest The authors declare that they have no known competing financial interests or non-financial (personal relationships) interests that could have appeared to directly or indirectly influence the work reported in this paper.

References

1. Goddin P (2014) Redefining uber: why the term rideshare doesn't fit. <https://mobilitylab.org/2014/04/17/redefining-uber-why-the-term-rideshare-doesnt-fit/>. Accessed 5 May 2019
2. Young M, Farber S (2019) The who, why, and when of uber and other ride-hailing trips: an examination of a large sample household travel survey. *Transport Res Part A*. 119:383–392
3. Henaio A, Marshall WE (2018) The impact of ride-hailing on vehicle miles traveled. *Transportation* 46(6):2173–2194
4. Khera S (2018) The demand for ride-sharing apps in India and why more people are using them. Retrieved from <https://www.thenewsminute.com/article/demand-ride-sharing-apps-india-and-why-more-people-are-using-them-84466>
5. Thelen K (2018) Regulating Uber: the Politics of the platform economy in europe and the United States. *Perspect Polit* 16(4):938–953
6. Silva LAS, Andrade MO, Maia ML (2018) How does the ride-hailing systems demand affect individual transport regulation? *Res Transp Econ* 69:600–606

7. Ko J, Lee S, Byun M (2019) Exploring factors associated with commute mode choice: an application of city-level general social survey data. *Trans Polic* 75:36–46
8. Nag D, BS M, Goswami A, Bharule S (2019) Framework for public transport integration at railway stations and its implications for quality of life. *SSRN Electron J*. <https://doi.org/10.2139/SSRN.3551888>
9. Hussain MS, Goswami AK, Gupta A (2022) Predicting pedestrian crash locations in urban India: an integrated GIS-based spatiotemporal HSID technique. *J Transport Safety Secur*. <https://doi.org/10.1080/19439962.2022.2048759>
10. J. d. D. Ortuzar and L. G. Willumsen. 2011 *Modelling Transport*, John Wiley & Sons, Ltd.,
11. Habib KN (2019) Mode choice modelling for hailable rides: An investigation of the competition of Uber with other modes by using an integrated non-compensatory choice model with probabilistic choice set formation. *Transport Res Part A* 129:205–216
12. Alemi F, Circella G, Mokhtarian P, Handy S (2019) Exploring the latent constructs behind the use of ridehailing in California. *J Choice Model* 29:47–62
13. Brodeur A, Nield K (2018) An empirical analysis of taxi, lyft and uber rides: evidence from weather shocks in NYC. *J Eco Behav Org* 152:1–16
14. Clewlow RR, Mishra GS (2017) *Disruptive Transportation: The Adoption, Utilization, and Impacts of Ride-Hailing in the United States*. University of California, Davis, Davis, Institute of Transportation Studies
15. Haddad EA, Vieira RS, Jacob MS, Guerrini AW, Germani E, Barreto F, M. L. Bucalem and. P. L. Sayon. (2019) A socioeconomic analysis of ride-hailing emergence and expansion in São Paulo, Brazil. *Transport Res Interdiscipl Perspect* 1:100016
16. Lavieri PS, Bhat CR (2019) Investigating objective and subjective factors influencing the adoption, frequency, and characteristics of ride-hailing trips. *Transport Res Part C: Emerg Technol* 105:100–125
17. Nguyen-Phuoc DQ, Su DN, Tran PTK, Le DTT, Johnson LW (2020) Factors influencing customer's loyalty towards ride-hailing taxi services – a case study of Vietnam. *Transp Res Part A Policy Pract* 134(February):96–112. <https://doi.org/10.1016/j.tra.2020.02.008>
18. Rayle L, Dai D, Chan N, Cervero R, Shaheen S (2016) Just a better taxi? A survey-based comparison of taxis, transit, and ridesourcing services in San Francisco. *Transp Policy* 45:168–178
19. Sarriera JM, Alesbury A (2017) To Share or Not To Share: Investigating the Social Aspects of Dynamic Ridesharing. *Transport Res Record* 2605(1):109–117
20. Tirachini A, Rio MD (2019) Ride-hailing in Santiago de Chile: users' characterisation and effects on travel behaviour. *Transp Policy* 82:46–57
21. Alemi F, Circella G, Mokhtarian P, Handy S (2019) What drives the use of ridehailing in California? Ordered probit models of the usage frequency of Uber and Lyft. *Transport Res Part C* 102:233–248
22. Mahmoudifard SM, Kermanshah A, Shabanpour R, Mohammadian A (2017) Assessing public opinions on uber as a ridesharing transportation system: explanatory analysis and results of a survey in Chicago area. In: *Transportation research board 96th annual meeting*. Transportation Research Board. Washington DC, United States. Retrieved from <https://trid.trb.org/view/1437517>
23. McDonald NC (2015) Are Millennials Really the “Go-Nowhere” Generation? *J Am Plan Assoc* 81(2):90–103
24. Lavieri PS, Dias FF, Juri NR, Kuhr J, Bhat CR (2018) A model of ridesourcing demand generation and distribution. *Transp Res Rec J Transp Res Board*. <https://doi.org/10.1177/0361198118756628>
25. Devaraj A, Ambi Ramakrishnan G, Nair GS, Srinivasan KK, Bhat CR, Pinjari AR, Ramadurai G, Pendyala RM (2020) Joint model of application-based ride hailing adoption, Intensity of Use, and Intermediate Public Transport Consideration among Workers in Chennai city. *Transp Res Rec* 2674(4):152–164. <https://doi.org/10.1177/0361198120912237>
26. Wang M, Martin E, Shaheen S (2012) Carsharing in Shanghai, China. *Transp Res Rec J Transp Res Board* 2319(2319):86–95. <https://doi.org/10.3141/2319-10>
27. Stiglic M, Agatz N, Savelsbergh M, Gradisar M (2018) Enhancing urban mobility: Integrating ride-sharing and public transit. *Comput Operat Res* 90:12–21
28. Yu B, Maa Y, Xue M (2017) Environmental benefits from ridesharing: a case of Beijing. *Appl Energ* 191:141–152
29. Erhardt GD, Roy S, Cooper D, Sana B, Chen M, Castiglione J (2019) Do transportation network companies decrease or increase congestion? *Sci Adv* 5(5):eaau2670. <https://doi.org/10.1126/sciadv.aau2670>
30. Circella G, Alemi F, Tiedeman K, Handy S, Mokhtarian P (2018) *The Adoption of Shared Mobility in California and Its Relationship with Other Components of Travel Behavior*. University of California, Davis, Davis
31. Kodransky M, Lewenstein G (2014) Connecting low-income people to opportunity with shared mobility. Retrieved from <https://trid.trb.org/view/1335548>
32. de Souza Silva LA, de Andrade MO, Alves Maia ML (2019) How does the ride-hailing systems demand affect individual transport regulation? *Res Transport Eco* 69:600–606
33. Simon Cheng JSL (2007) Testing for IIA in the Multinomial Logit Model. *Soc Method Res* 35(4):583–600
34. Hensher DA, Stopher PR (1979) *Behavioural travel modeling*. Taylor and Francis Group, Routledge. Retrieved from <https://www.routledge.com/Behavioural-Travel-Modelling/Hensher-Stopher/p/book/9780367740870>
35. Acheampong RA, Siiba A, Okyere DK, Tuffour JP (2020) Mobility-on-demand: an empirical study of internet-based ride-hailing adoption factors, travel characteristics and mode substitution effects. *Transport Res* 115:102638
36. Deepa L et al (2022) An analysis of individuals' usage of bus transit in Bengaluru, India: Disentangling the influence of unfamiliarity with transit from that of subjective perceptions of service quality. *Travel Behav Soc* 29:1–11. <https://doi.org/10.1016/J.TBS.2022.05.001>
37. V. B. Krishnan, “How the nature of Indian families is changing.” 04 July 2019. [Online]. Available: <https://www.thehindu.com/news/national/how-the-nature-of-indian-families-is-changing/article28281107.ece>.
38. Z. Shaikh, “Rural India starts to go nuclear, urban families grow in shrinking space.” *The Indian Express*, 06 July 2017. [Online]. Available: <https://indianexpress.com/article/india/rural-india-starts-to-go-nuclear-urban-families-grow-in-shrinking-space-4737882/>.
39. "More than 50% of India's population is now 25 years or older," 03 July 2020. [Online]. Available: <https://www.livemint.com/news/india/more-than-50-of-india-s-population-25-yrs-or-older-survey-11593793054491.html>.
40. Statista, "Smartphone penetration rate in India from 2010 to 2020, with estimates until 2040," [Online]. Available: <https://www.statista.com/statistics/1229799/india-smartphone-penetration-rate/#:~:text=Smartphone%20penetration%20rate%20in%20India%202010%2D2040&text=In%202020%2C%20the%20penetration%20rate,total%20population%20were%20using%20smartphone..>
41. India Today, "Ola, Uber say no surge pricing during odd-even scheme in Delhi," 02 November 2019. [Online]. Available: <https://www.indiatoday.in/india/story/ola-uber-say-no-surge-pricing-during-odd-even-scheme-in-delhi-1615005-2019-11-02>.

42. CNN Money, "Singapore slaps limit on the number of cars on its roads," 24 October 2017. [Online]. Available: <https://money.cnn.com/2017/10/24/news/singapore-car-numbers-limit/index.html>.
43. Nimesh V, Kumari R, Soni N, Goswami AK, Mahendra Reddy V (2021) Implication viability assessment of electric vehicles for different regions: an approach of life cycle assessment considering exergy analysis and battery degradation. *Energy Convers Manag.* <https://doi.org/10.1016/J.ENCONMAN.2021.114104>

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