Joint Model of App-Based Ridehailing Adoption, Intensity of Use and Intermediate Public Transport (IPT) Consideration among Workers in Chennai City

Aravinda Devaraj
Research Scholar (M.S.)
Department of Civil Engineering
Indian Institute of Technology Madras
Chennai, Tamil Nadu, India, 600036
Email: aravindadevaraj@gmail.com

Ganesh Ambi Ramakrishnan (corresponding author)
Research Scholar (Ph.D.)
Department of Civil Engineering
Indian Institute of Technology Madras
Chennai, Tamil Nadu, India, 600036
Email: ambi.ganesh@gmail.com

Gopindra Sivakumar Nair
Research Scholar (Ph.D.)
The University of Texas at Austin
Department of Civil, Architectural and Environmental Engineering
301 E. Dean Keeton St. Stop C1761
Austin TX 78712, USA
Tel: 1-512-200-5884, Fax: 1-512-475-8744,Email: gopindra@utexas.edu

Karthik K. Srinivasan
Professor
Department of Civil Engineering
Indian Institute of Technology Madras
Chennai, Tamil Nadu, India, 600036
Email: karthikks@iitm.ac.in

Chandra R. Bhat
Professor
The University of Texas at Austin
Department of Civil, Architectural and Environmental Engineering
301 E. Dean Keeton St. Stop C1761
Austin TX 78712, USA
Tel: 1-512-471-4535, Fax: 1-512-475-8744, Email: bhat@mail.utexas.edu
and
The Hong Kong Polytechnic University, Hung Hom, Kowloon, Hong Kong

Abdul R. Pinjari
Associate Professor
Department of Civil Engineering
Center for infrastructure, Sustainable Transportation and Urban Planning (CiSTUP)
Indian Institute of Science (IISc)
Bangalore 560012, India
Ph: +91-80-2293 2043; Fax: +91-80-2360 0404
Email: abdul@civil.iisc.ernet.in

Gitakrishnan Ramadurai
Associate Professor
Department of Civil Engineering
Indian Institute of Technology Madras
Chennai, Tamil Nadu, India, 600036
Email:gitakrishnan@iitm.ac.in

Ram M. Pendyala
Professor
Arizona State University, School of Sustainable Engineering and the Built Environment
660 S. College Avenue, Tempe, AZ 85287-3005
Tel: 480-727-4587; Email: ram.pendyala@asu.edu

ABSTRACT

The introduction of app-based ridehailing (RH) services represents a convergence between technologies, supply of vehicles and demand in near real-time. There is growing interest towards quantifying the demand for such services from regulatory, operational, and system evaluation perspectives. Several studies model the decision to adopt and the extent of use of RH, either separately or by bundling them into a single chice dimension, disregarding potential endogeneity between these decisions. Unlike developed countries, the literature is sparser regarding RH in developing countries, where the demand may differ considerably due to differences in vehicle ownership, and availability and patronage of many transit and Intermediate Public Transport (IPT) modes (carrying 40% shares in some cases).This study aims to bridge these gaps in the literature by investigating three inter-related choice dimensions among workers in Chennai city: adoption of RH, their subsequent usage intensity, and the consideration of IPT modes. The main factors influencing these decisions are identified by estimating a trivariate probit model.

The results indicate that socio-demographic and locational characteristics and the availability of IPT modes influence RH adoption, whereas, work-related constraints, and perception of other modes affect its frequency. Work and non-work characteristics affect both dimensions. Further, endogeneity is observed between RH and IPT adoption even after controlling for these variables, whereas evidence of endogeneity is absent among other dimensions. Implications for demand analysis of RH and its applications for planning in the developing country context are discussed.

Keywords: app-based ridehailing, trivariate ordered probit model, adoption, frequency, consideration, Intermediate Public Transport, auto-rickshaw, share-auto

INTRODUCTION

Ridehailing services aim to bridge the gap between personal and public transport by offering reliable, comfortable, on-demand, end-to-end travel without the hassle of owning and driving a personal vehicle. These services have the potential to influence individual travel behavior, ridership of other modes and the overall transport system. Existing studies investigate the interaction between usage of ridehailing services with the usage of other modes such as personal vehicles and public transit to capture the potential mode shift across these modes.

The wide range of differences in user segments and usage contexts across different geographies makes it difficult to conclude how and when ridehailing services substitute or supplement rides from the other modes. For example, Indian cities have some distinct transport system characteristics such as lower auto-dependency but rapidly growing vehicle ownership, overcrowded and declining public transit modes and a slew of paratransit or intermediate public transport (IPT) options such as auto-rickshaws and taxi operators. The demand for ridehailing services and existing modes may also vary in Indian cities from other developed countries due to differences in socio-demographic and technology literacy characteristics. Given the rapid adoption of RH, its impacts on system performance including congestion, pollution remain to be better understood. In this context, this study aims to investigate the demand for RH services among the Indian commuters.

App-based ridehailing services (RH) integrate passengers with nearby drivers using an online platform provided by "aggregator" companies. Existing IPT modes such as auto-rickshaw, share-auto, tuk-tuk etc. have been providing on-demand mobility albeit without the technological interface. IPT modes can serve short or local trips, offer first and last-mile connectivity to transit stations, or point-to-point mobility within the city. As these modes share many service characteristics with ridehailing alternatives, there is a need to model the demand for IPT and ridehailing services jointly.

Usage rates of ridehailing services are found to vary across different segments and are highly context specific (non-work, weekend travel and late night return home, or access to intercity terminals). However, the influence of work-related characteristics and constraints have received less attention. Besides the role of other contextual variables such as trip chaining, unplanned trips, carrying heavy objects etc. are also not adequately investigated.

In the light of these motivating considerations and gaps in the literature, the broad objective of this paper is to jointly model three inter-related decisions: 1) adoption of ridehailing services, (2) their usage frequency and (3) the consideration of other IPT modes (auto-rickshaw, share-auto and company bus). The specific research issues investigated include:

1. Identify factors that influence ridehailing adoption and differentiate them from those that affect the intensity of usage among workers in Chennai city
2. Investigate the nature and extent of interaction between consideration of IPT modes and ridehailing choice dimensions above at systematic and unobserved levels
3. Examine the role of work and non-work characteristics in determining RH adoption and usage frequency.
4. Analyze whether and how attributes of existing modes influence the demand for ridehailing

A joint trivariate ordered probit model system is developed to account for possible endogeneity among the three choice dimensions (two binary and one ordinal response) and address the research issues above. The models are estimated using data from a random sample of 804 workers in Chennai city.

This study contributes to and is distinct from the growing body of work on RH in the following respects: evidence of interdependence between RH adoption and IPT consideration is observed at systematic and unobserved levels, whereas, no evidence of selectivity is seen between RH adoption and intensity of use. Some common variables have different impacts on the two RH choice dimensions Constraints from work and non-work-related activities defining the time use patterns of workers (such as departure time to work, duration of work, the intensity of shopping activities, joint travel, travel at odd times etc.) are significant determinants of both ridehailing choice dimensions.

A brief review of the related literature is presented in the next section. The data description and preliminary analysis are presented followed by a discussion of model formulation and results. The final section summarizes the salient findings and proposes some directions for future research.

REVIEW OF LITERATURE

A brief review of literature on the demand for ridehailing services and usage of IPT is presented in this section. While ridehailing services have grown in popularity as well as fleet size, their mode share is still too low for usual or routine trip-making. The demand for these services is commonly captured by modelling their adoption or usage intensity. The common findings from studies across multiple cities show that ridehailing adoption and usage rates are higher among young, well-educated and well-paid urban residents. A higher propensity to use such services is attributed to a tech-savvy, environmentally conscious lifestyle with openness to use multiple modes for travel (*1–3*) and a lower personal vehicle ownership (*4*).

The frequency of use of ridehailing services has been widely documented through descriptive statistics but modelled in fewer studies. Among those that model the usage frequency, most studies (*1*, *3*, *5*) specify non-usage as the lowest level in the ordinal variable for ridehailing usage frequency. Lavieri and Bhat (*2*) jointly model the experience of having used a pooled or solo trip and overall usage frequency, among other choice dimensions. They allow for correlation between the two but do not disentangle the decision to not use ridehailing at all (zero trips) from the subsequent usage frequency levels. Other studies address the issue of selectivity, but in a mode choice context (*6*) or within a choice based sample (*7*). Alemi et al. (*8*) address this issue between adoption and usage frequency through sample selection and zero-inflation models and find evidence of selectivity. They note that demographic characteristics influence only the adoption level and not frequency of use.

Especially in the case of a new transport alternative such as ridehailing, some exogenous factors affecting the intensity of use may be less relevant or have a different effect on those who have not adopted it. Further, common unobserved factors may affect both levels leading to biased estimates and forecasts. Hence, it is necessary to distinguish between the adoption of ridehailing services from their usage intensity while allowing for selectivity effects.

Many studies on ridehailing are based developed country contexts, where the choice is typically between cars, transit, paid and app-based cab services (*4*, *9*). But, in the context of Asian cities, a number of Intermediate Public Transport (IPT) modes (such as auto-rickshaws, e-rickshaws, share-autos, tuk-tuk etc.) have been providing on-demand services, but without the technological features and may share similar operating characteristics (coverage, flexibility etc.). Unfortunately, there is relatively less data and studies on their demand or the usage patterns (*10*). As the ridehailing operations in Indian context includes not only cars but also auto-rickshaws, the demand for such services are also likely to be intertwined with the demand for conventional IPT modes which has not been adequately investigated.

Intermediate Public Transport modes are similar to public transport in that they provide mobility as a service rather than a product, and yet offer flexible, comfortable, and door-to-door travel (in some cases) like personal vehicles (*11*). In the context of Chennai city, IPT includes auto-rickshaw and shared-autos as well as chartered buses and company bus services provided by the employer.

The focus of the existing studies on IPT modes in India has has been on user segments, mode choice relative to transit, and user perception of service attributes whereas the relationship to RH has not received much attention. Auto-rickshaws are three-wheelers which carry 5-20% mode shares in some Indian cities (*12*) whose user base consists more of women and middled-age commuters (*13*). Fare non-compliance and ride refusal have been repeatedly highlighted in multiple studies as top issues in travel by auto-rickshaws (*14–17*). Shared-autos are larger four-wheelers with a seating capacity of seven which ply on selected fixed routes that overlap with bus routes and its user base consists of students and younger commuters (*18*), and are cheaper than auto-rickshaws.

Among the few studies that compare IPT and ridehailing, Basu et al. (*19*) identified traditional IPT users as being more cost-sensitive and less comfortable with modern technology. Ridehailing users were more sensitive to comfort, reliability and driver behaviour, and had a higher willingness to pay for these conveniences. Traditional IPT modes served a higher share of mandatory trips while ridehailing services were used more for trips to the airport. However, potential endogeneity between the choice of IPT and ridehailing modes is not captured.

Other studies that allow for interaction between the choice of ridehailing and other modes at the unobserved level are limited to other similar technology-intensive services such as ridesharing or carpooling (*3*, *4*). Although some studies identify the different user segments of ridehailing modes, they do not map their preference for the new services to their perception or evaluation of existing modal alternatives. Hence, although these studies identify general trends of mode shift, the specific modal attributes contributing to this shift are not identified.

Many studies reveal that ridehailing services are predominantly used for social or recreational trips and less so for commute and personal errands (*2*, *19–21*). Lavieri and Bhat (*2*) jointly model the purpose, time of day and other activity characteristics of ridehailing trips but do not distinguish the usage frequency decision itself by trip purpose. Young and Farber (*21*) highlight that the introduction of ridehailing services has a negligible impact on overall mode shares but a significant shift for non-commute trips among young individuals. Xie et al. (*7*) highlight how full-time workers differ from others in their sensitivities to travel time and cost of ridehailing modes. However, the influence of differences across trip purposes on ridehailing intensity or the effect of work-related constraints on the adoption and use of ridehailing services are not sufficiently investigated.

This study aims to address the following gaps noted in the literature:

(1) There is limited understanding of the factors influencing the adoption and use of ridehailing services in developing countries in the light of multiple public transport and IPT alternatives available.
(2) Existing studies have not sufficiently explored the difference between adoption and subsequent usage of these services.
(3) Potential endogeneity between adoption, frequency of ridehailing and IPT usage has not been adequately investigated
(4) The role of such contextual influences and work and non-work characteristics on the demand for ridehailing services is not well understood.

DATA DESCRIPTION AND EXPLORATORY ANALYSIS

The data for this study is collected from a random sample of nearly 900 workers in Chennai city using face-to-face interviews in 2015-2016. The survey questionnaire contains questions regarding socio-demographics, work-commute and other travel patterns as well as usage and attributes of various modes.

After data cleaning, a total of 804 usable responses were obtained. The primary socio-demographic variables in the sample such as household size, gender and vehicle ownership were in reasonable agreement with the census values in 2011. The average household size of a worker in this study is 4 (census value is 4.10) and nearly 82% of the workers are male (in population is 78%). The average vehicle per household in the sample was 1.44 versus 1.26 in 2008 (*22*). Nearly two-thirds of the sample earn below Rs. 20,000 per month while only 10% of the workers earn more than Rs. 60,000.

Respondents were asked if they had used app-based ridehailingservices for any purpose in the previous three months. Non-usage in the three-month period is referred to as non-adoption of ridehailing services. Similarly, respondents were also asked whether they had used auto-rickshaw, share-auto or company bus for work in previous three months. The respondents who reported using ridehailing services were asked for the frequency of use on an ordinal scale.

Nearly 43% of the sample had used ridehailing services which is comparable to 52% who reportedly used bus in the three month period. Among those adoptingridehailing services, 54% had a frequency of 1-2 times, 24% used it 3-5 times and and the remaining 20% was split equally between 6-10 and more than ten times, indicating infrequent among most respondents. In comparison, 74.25% of respondents considered IPT, but only 10% used it as the primary commute mode, indicating that both IPT and ridehailing are rarely used for work trip.

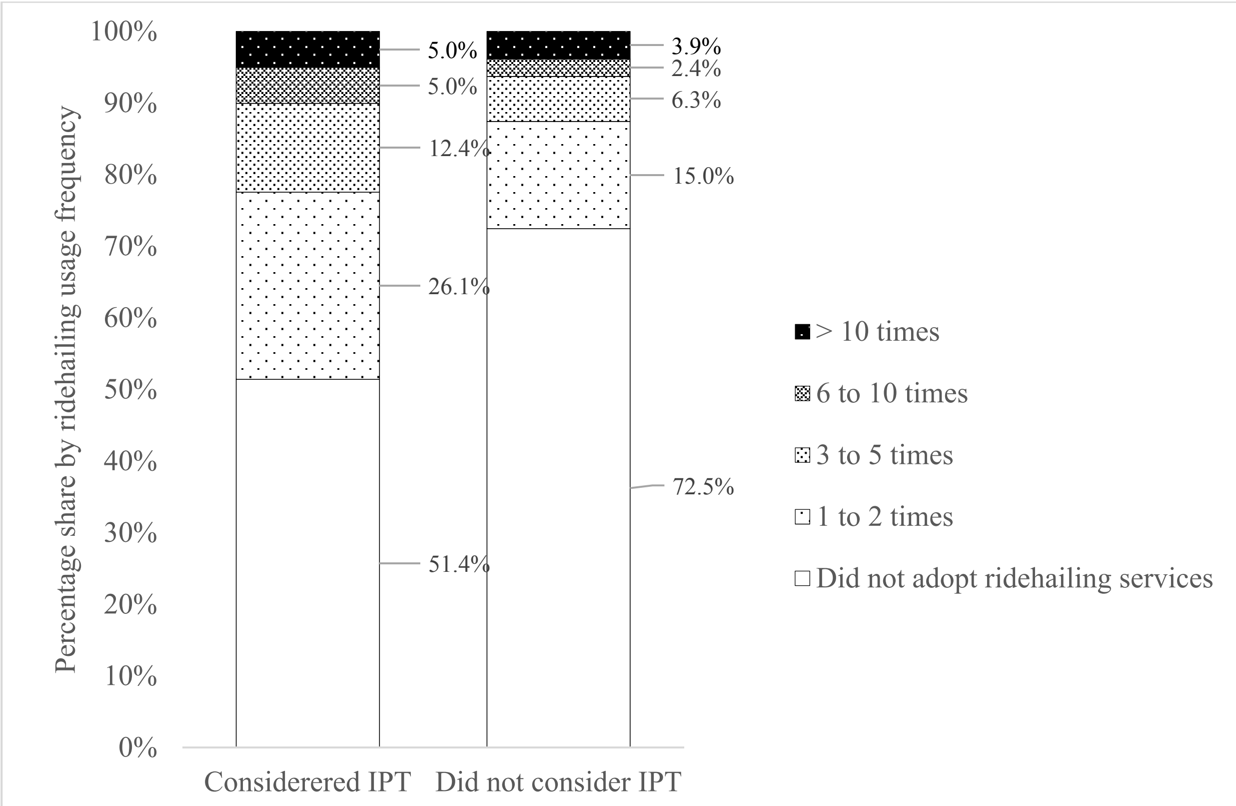

Figure 1 Distribution of RidehailingFrequency versus IPT Consideration

Figure 1shows clear differences in frequency of RH use across those who conider IPT versus those who do not. Among those who considered IPT, the share of workers who did not adopt ridehailing services is less compared to workers who did not consider IPT. At the other extreme, 10% of workers who considered IPT use ridehailing services frequently (6+ times) compared to 6.3% of workers among the others. A chi-squared test (not shown due to space limitation) rejects the hypothesis that ridehailing adoption and IPT consideration are independent, whereas, independence of RH frequency and IPT consideration can't be rejected.

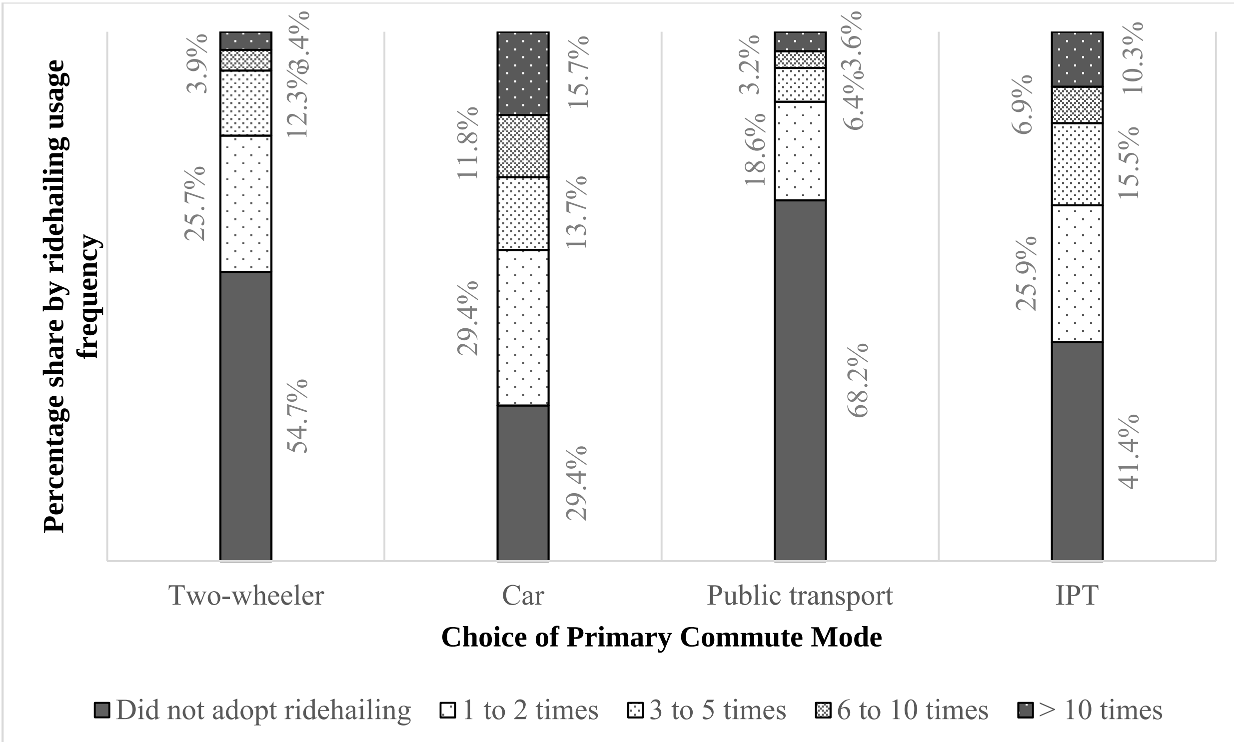

Figure 2 Distribution of RidehailingFrequency VersusPrimary Mode Chosen for Work

A plot of RH frequency distribution versus primary mode for work (Fig.2) reveals interesting differences. Ridehailing adoption is higher among car and IPT mode users than two-wheeler and public transport users.The share of commuters having a high usage frequency of ridehailing services (at least 6 times in three months) is highest among car users followed by IPT modes. The differences in the share of workers adopting ridehailing services among those who use two-wheeler and car suggests that the type of personal vehicle used for work matters in developing countries. A chi-square test for independence between ridehailing frequency and primary modes (car, IPT and other motorized modes) confirms this dependence between these two dimensions.

Thus, these exploratory analyses suggests that the IPT consideration, primary work mode characteristics and ridehailing adoption and frequency are positively associated and need to be modeled in conjunction with each other.

JOINT MODEL SPECIFICATION AND ESTIMATION

The three dimensions of interest in this study are consideration of IPT, ridehailing adoption and intensity. Since the intensity of use of ridehailing is observed only among those who have adopted these services, while we also observed significant interdependence among ridehailing adoption and IPT consideration, we develop a joint model to account for sample selection between ridehailing adoption and intensity of use of ridehailing services while simultaneously capturing the endogeneity at unobserved levels between ridehailing adoption and IPT consideration.

The utility of IPT consideration (U_1), ridehailing adoption (U_2) and ridehailing frequency (U_3) and the associated response variables for an individual is specified as follows:

$$U_1 = \beta_1 X_1 + \varepsilon_1 \tag{1}$$

$$U_2 = \beta_2 X_2 + \varepsilon_2 \tag{2}$$

$$U_3 = \beta_3 X_3 + \varepsilon_3 \tag{3}$$

$$Y_1 = \begin{cases} 1, \ if \ IPT \ is \ considered \\ 0, \ Otherwise \end{cases} \tag{4}$$

$$Y_2 = \begin{cases} 1, \ if \ ridehailing \ adoption \\ 0, \ Otherwise \end{cases} \tag{5}$$

$$Y_3 = \begin{cases} 0, if \ Y_2 = 0 \\ 1 \ (very \ low), ridehailing \ frequency \ is \ 1-2 \ times \ in \ three \ months, if \ Y_2 = 1 \\ 2 \ (low), ridehailing \ frequency \ is \ 3-5 \ times \ in \ three \ months, if \ Y_2 = 1 \\ 3 \ (moderate), ridehailing \ frequency \ is \ 6-10 \ times \ in \ three \ months, if \ Y_2 = 1 \\ 4 \ (high), ridehailing \ frequency \ is > \ 10 \ times \ in \ three \ months, if \ Y_2 = 1 \end{cases} \tag{6}$$

Thus, non-zero values of Y_3 are observed only when $Y_2 = 1$ and hence the two dimensions Y_2 and Y_3 are likely to be endogenous due to possible self-selection effect. Also, Y_1 and Y_2 as well as Y_1 and Y_3 are likely to be endogenous due to simultaneity with possible common observed and unobserved factors affecting these choices.

Where, X_1, X_2 and X_3 are the set of explanatory factors affecting the corresponding choice dimensions and β_1, β_2 and β_3 indicate their corresponding coefficients. The error components are assumed to follow trivariate normal (TVN) distribution with zero mean and unit variance.

$$(\varepsilon_1, \varepsilon_2, \varepsilon_3)^T = TVN(0, \Sigma), \Sigma = \begin{pmatrix} 1 & \rho_{12} & \rho_{13} \\ \rho_{12} & 1 & \rho_{23} \\ \rho_{13} & \rho_{23} & 1 \end{pmatrix} \tag{7}$$

Likelihood formulation

Case 1: Ridehailing is not adopted

In this case, IPT may or may not be considered (i.e. $Y_1 = 0$ or 1), but $Y_2 = 0$ and $Y_3 = 0$. The likelihood for these two outcomes (i.e. $Y_1 = 0$ or 1, $Y_2 = 0$) is expressed as:

$$P(Y_1 = \delta_1, Y_2 = 0, Y_3 = 0) = P((2\delta_1 - 1)U_1 \geq 0, U_2 \leq 0) = \int_{\varepsilon_1 = -\infty}^{(2\delta_1 - 1)\beta_1 X_1} \int_{\varepsilon_2 = -\infty}^{-\beta_2 X_2} \phi_2((2\delta_1 - 1)\varepsilon_1, \varepsilon_2, (2\delta_1 - 1)\rho_{12}) d\varepsilon_1 d\varepsilon_2 \tag{8}$$

This case corresponds to two possible outcomes (IPT considered and ridehailing not adopted) and (IPT not considered and ridehailing not adopted). Where, δ_1 is 1 for those who considered IPT and 0 otherwise.

Case 2: Ridehailing is adopted

In this case, again IPT may or may not be considered as in case 1, but $Y_2 = 1$ and $Y_3 > 0$. The corresponding likelihood is expressed as:

$$P(Y_1 = \delta_1, Y_2 = 1, Y_3 = k) = P\big((2\delta_1 - 1)U_1 \geq 0, U_2 \geq 0, \mu_{k-1} \leq U_3 \leq \mu_k\big) = \int_{\varepsilon_1 = -\infty}^{(2\delta_1 - 1)\beta_1 X_1} \int_{\varepsilon_2 = -\infty}^{\beta_2 X_2} \int_{\varepsilon_3 = \mu_{k-1} - \beta_3 X_3}^{\mu_k - \beta_3 X_3} \phi_3\big((2\delta_1 - 1)\varepsilon_1, \varepsilon_2, \varepsilon_3, (2\delta_1 - 1)\rho_{12}, (2\delta_1 - 1)\rho_{13}, \rho_{23}\big) d\varepsilon_1 d\varepsilon_2 d\varepsilon_3 \tag{9}$$

Equation 9 corresponds to eight possible outcomes (IPT adopted or not, frequency level is very low, low, medium and high). Where, $\phi_2(.)$ and $\phi_3(.)$ represents the bivariate and trivariate standard normal density function. ρ_{12}, $\rho_{13}$and $\rho_{23}$are the pairwise correlation between corresponding choice dimensions, $\mu_{k-1} = -\infty$ for $k = 1$ and $\mu_k = \infty$ for $k = K$.

Thus **Equations 8 and 9** can be generalized to form the joint likelihood for the three choice dimensions are can be written as follows.

$$L = \prod_{n=1}^{N}\left(\prod_{i=0}^{1}\prod_{j=0}^{1}\prod_{k=0}^{K}[P(Y_{1n} = i, Y_{2n} = j, Y_{3n} = k)]^{\delta_{ijkn}}\right) \quad (10)$$

Where *n* is the index for the worker, i and j are the binary indicator for IPT consideration and ridehailing adoption respectively and *k* represents the number of levels of frequency (K = 4 in this study). Note that **Equation 10** applies only to the two outcomes in case 1, and 8 outcomes in case 2. All parameters are estimated simultaneously by maximizing the joint likelihood expression given in **Equation 10** using GAUSS software.

RESULTS

The results of the joint model are presented in **Tables 1** and **2**. A significant error correlation (+0.257) is observed only between the consideration of IPT and adoption of ridehailing ridehailing. The results of these two choice dimensions are presented in **Table 1**. Details of the factors affecting each choice dimension are presented in the following subsections. In comparison to the independent models (all correlations constrained to zero), the joint model shows a significant improvent in the overall goodness of fit (chi square of 12.4 for three degrees of freedom, significant at 95% confidence level). In comparison to the independent models, coefficients for‘travel at odd times’, ‘no driving knowledge’, ‘took bus or train work’ and ‘monthly expenses on auto-rickshaws’ we reduced by at least 10% in the ridehailing adoption component, while the alternative specific constantsfor IPT consideration andridehailing adoption increased by 5% and 3% respectively. Since the frequency of ridehailing was uncorrelated with the other two dimensions, the parameterestimates in this part of the modelremained largely unaffected. However, only the variable indicating sensitivity to loss of productive time while driving lost significance in the joint model.

At the observed level, a higher sensitivity to time or presence of workplace-induced temporal constraints characterises the users of both IPT and ridehailing services. However, workers commuting during the morning peak show a preference for IPT modes whereas those commuting later may consider either of the two services. This difference may be a result of the variation in the supply side characteristics of IPT services themselves (frequency of share auto services decreases and fare of auto-rickshaws increases beyond 9:00pm).

Other common characteristics observed in users of both services include younger age, higher income level and the availability of company bus services at work. Interestingly, the above factors are also characteristic of workers in the IT sector and hence may also reflect the role of a technology-intensive work environment and lifestyle. Hence more detailed information on the nature of work in future studies may help capture the effect of work-related lifestyle characteristics on the adoption of these new modes.

The lack of driving knowledge has a negative influence on ridehailing adoption in contrast to its positive role in the consideration of IPT modes. It is likely that this contrast is a reflection of higher cost sensitivity among those who lack driving knowledge and consequent preference for economical IPT modes such as share auto or company bus. This claim needs to be investigated through more careful analysis of preference within IPT modes and valuation of the associated cost sensitivities with larger data sets in the future.

TABLE1 Results of the IPT Consideration and Ridehailing Adoption Model Components

Variables	Joint Model			
	IPT consideration: (base: not considered)		Ridehailing adoption: (base: not adopted)	
	Coeff.	t-stat	Coeff.	t-stat
Constant	0.447	1.93	-0.795	-3.14
Activity characteristics				
Penalty for late arrival: Half day pay cut	0.661	2.19		
Carries heavy luggage	0.535	3.33		
Vehicle owner * perceived lack of productive time use while driving	0.403	2.77		
Vehicle owner*leaves for work after AM peak (post 11:00am)	0.823	1.51**		
Stressful to travel by PV during morning peak			0.310	2.45
Leaves for work very early or very late (between 5:00pm to 6:00am)			0.393	1.42*
Frequently travels at odd times			0.196	1.64
Makes atleast 2 trips in addition to commute daily			0.233	1.51**
Travels with a copassenger			0.260	2.02
Personal vehicle ownership and use				
No Driving knowledge	0.435	2.11	-0.319	-1.59**
Number of cars per working member in the household			-0.289	-1.66
household with one two-wheeler and no car			-0.251	-1.79
Doesn't own a vehicle			-0.349	-1.75
Availability, usage and perception of other shared modes				
Share auto non-availability	-0.214	-1.74		
Lives within 2km of rly stn and took trn to work in 3 months	0.333	2.21		
Took bus to work in three months	0.602	5.17		
Employer provides company bus	1.000	5.18	0.822	5.72
Monthly expense on Auto (in Rs. 100)			0.020	1.48**
Auto fare: Not compliant with meter			0.292	2.65
Took train to work in three months but not bus			0.329	1.77
Took bus and train to work in three months			-0.203	-1.60**
Frequency of alternate (second most commonly used) mode 3 or more times a month			0.257	2.19
Location characteristics				
Residing within 5km from workplace			-0.214	-1.69
Lives and works in urban area			-0.324	-1.63**
Lives in non-urban area and works in urban area			-0.389	-1.67
Lives in urban area and works in non-urban area			-0.734	-3.37
Socio-demographic Characteristics				
Male workers	-0.293	-1.84		

Age of the worker (continuous)	-0.008	-1.54**		
Age of the worker: 46 and above			-0.276	-1.91
Income above Rs.20,000	0.237	1.97		
Income: Rs.20,001-60,000 per month			0.412	3.36
Income: Rs.60,001 per month and above			0.879	4.43
Edu-UG and above			0.614	4.83
Self employed			1.087	3.27
Correlation coefficients				
IPT use and ridehailing adoption	0.257	3.17		
Ridehailing adoption and ridehailingfrequency	-0.120	*-0.99*		
IPT use and ridehailingfrequency	-0.083	*-0.39*		
MODEL STATISTICS				
Initial log likelihood	LL(0)	-1595.625		
Converged log likelihood	LL(M)	-1146.539		
Likelihood ratio	Rho Sq.	0.281		
Chi squared improvement due to correlation (df=1)	chi sq.	12.397		
Number of observations		804		

'*' represents variables significant at 85% one-sided, '**' for 90% one sided, italicized t-stat are insignificant at 85% one-sided, all other variables are significant at 95% one-sided, 'n/a' = not applicable

Consideration of Intermediate Public Transport

Several factors relating to departure time of work trip, penalty for late arrival at work, and trip context are found to influence consideration of IPT. They are more likely to be considered by time-sensitive workers and those working under strict timing constraints, i.e., workers who face stiff penalty for late arrival (half-day pay cut) were more likely to consider IPT modes. Workers sensitive to the loss of productive time due to driving are also more likely to consider them. This variable is significant only among vehicle owners as they are more likely to drive regularly. Vehicle owners who depart for work in the post a.m. peak (in the second or later shifts) are more likely to consider IPT as transit services may be unavailable or less frequent whereas household personal vehicles may be allocated to others leaving earlier. IPT modes are also more likely to serve or substitute the usual modes of workers who frequently carry heavy luggage during commute since such travel would be difficult by public transport or other shared modes.

While auto-rickshaws are widely available through\out Chennai city, shared-autos and company bus are available only on limited routes or selected destinations. As expected, the lack of coverage by share autos decreases the probability of IPT consideration while availability of company bus services increases it.

Interestingly, the availability of other modes also influence IPT consideration. Workers living within 2km of a railway station and considering train and those considering bus for their daily commute are more likely to consider IPT than others. The positive influence may reflect a greater openness towards using shared modes including some IPT services or that IPT often serves as access or egress modes to transit in some cases. It is noted that these effects can't be attributed to captivity due to lack of vehicle ownership or driving knowledge, but are significant even after controlling for them. Contrary to the common perception that transit users mostly belong to captive segment, the finding suggests that such workers are more flexible in trip-making as they consider multiple modes (transit and IPT).

Women are more likely to consider IPT modes than men. This may be attributed to a greater valuation of privacy and personal security offered by paid-private IPT alternatives such as auto-rickshaws or semi-private options such as company buses (shared with other employees of the same establishment).

Adoption of Ridehailing Services

Access to personal vehicle (ownership and driving knowledge) has a significant influence on ridehailing adoption. However, two major trends are observed that are different from findings in existing literature. Contrary to findings from prior studies, adoption of ridehailing is positively correlated with a higher number of vehicles in the household (+0.21). However, differentiating between the types of vehicle owned reveals that this contrast is attributable to two-wheeler ownership.

Among car owners, as the number of cars per worker in the household increases (increasing access to a comfortable personal mode) the probability of adopting ridehailing services decreases. On the other hand, the propensity to use ridehailing increases with two-wheeler ownership among non-car owners. Since two wheelers are more affordable, most households own at least one two-wheeler. The presence of a second or third two-wheeler is more likely in the higher income groups. In this case, higher vehicle ownership may a higher household economic level irrespective of the worker's individual income. Workers lacking driving knowledge are likely to have greater familiarity with the existing public transit and IPT services due to their captivity to non-personal alternatives and hence, have a lower probability of adopting ridehailing services. While this identifies non car-owners, as an important user segment, deeper analysis may be necessary to identify whether and to what extent their ridehailing trips are being substituted from other modes or newly induced.

Workers leaving for work during 8:00 to 11:00 a.m. which straddles the morning peak and find travelling by personal vehicle stressful are more likely to adopt ridehailing services which offer comparable comfort and privacy but without the driving stress. Workers who leave for work in the early (before 6:00am) or late hours (after 5:00pm) of the day are also more likely to adopt ridehailing as are those who frequently have to travel at odd times for work and other trips, perhaps due to lower wait times or coverage than transit during lean periods.

Joint travel during commute contributes positively to the adoption probably due to convenience and cost advantage in group over solo travel. The ridehailing adoption probability is also higher for workers who make at least 2 trips (other than work commute). Such workers may more constrained for time or in need of a comfortable substitute to their regular mode to decrease the strain of their additional travel.

Workers who leave for work between 8:00 and 11:00 a.m. (which straddles the morning peak) and find travelling by personal vehicle stressful are more likely to adopt ridehailing services which offer comparable comfort and privacy but without the driving stress. Workers who leave for work in the early (before 6:00am) or late hours (after 5:00pm) of the day and those who frequently travel at odd times for work or other trips are more likely to adopt ridehailing, perhaps due to lower wait times for these services or lower coverage of transit during lean periods.

Joint travel during commute contributes positively to ridehailing adoption probably due to convenience and cost advantage in group travel over solo travel. The ridehailing adoption probability is also higher for workers who make at least two trips (other than work commute). Such workers may be more constrained for time or in need of a comfortable substitute to their regular mode to decrease the strain of their additional travel.

Workers who use more than one commute mode and use it at least three or more times a month have a greater likelihood of adopting ridehailing. The tendency to consider emerging mobility modes is thus impeded by inertia or habit associated with primary work mode. On the other hand, workers employed in establishments that offer company bus services are more likely to adopt ridehailing services perhaps as an alternative means of travel while returning home from work or when departure times from work or home vary from the usual timings.

In contrast to workers who took both bus and train to work in the past three months, those who took train but not bus were more likely to adopt ridehailing. This may reflect the use of ridehailing for last or first mile connectivity to train in places where bus service is either infrequent or offers inadequate linkages to train network. In places where both are available, the need for such ridehailing may diminish. On the other hand, train-only users may be more sensitive to reliability which may also favour the consideration of ridehailing, whereas those who also use bus may be more cost sensitive.

Workers who face issues of fare non-compliance by auto-rickshaw drivers are more likely to adopt ridehailing services. This factor is an important indicator of a potential mode shift from the regular auto-rickshaw to ridehailing alternatives as multiple studies have reported fare non-compliance as the top disadvantage of using auto-rickshaws in Indian cities. Ensuring compliance may help retain the ridership of this user segment with the existing IPT modes. Further, workers whose monthly expenditure on auto-rickshaws is higher also have a positive coefficient. This could indicate a higher willingness to pay for private, on-demand mobility while being sensitive to the transparency of the fare structure.

Location of the residence and workplaces are reflective of proximity to different activity centres. Compared to workers who live and work in non-urban areas, commuters who live or work in urban localities are less likely to adopt ridehailing services. This is in spite of the fact that the supply of ridehailing services were more concentrated in urban areas at the time of the study. This may be due to the greater availability or better levels of service of other modes such as transit compared to non-urban areas. In this context, note that no discernible evidence of difference in IPT adoption is seen based on these home and work location variables.

Besides, since the urban areas have a higher density of activity centres than non-urban areas, i.e. shorter trip lengths, other modes that are more economical over shorter distances may be preferred. Non-urban residents may have to travel longer distances for many of their activities. In case of commute distance, workers living within 5km of their workplaces are less likely to adopt ridehailing services. The cost per kilometre for ridehailing services decreases with increasing trip distance. Hence, they offer more cost-effective mobility solutions over longer distances and hence may have a higher adoption probability among non-urban residents.

Older workers are less likely to adopt ridehailing as they may have lower access to or familiarity with the smartphone technology required to access these services. As is seen in other cities, higher propensity to adopt ridehailing is associated with higher individual income and educational qualifications. Self-employed individuals are more likely to adopt ridehailing services. Such workers may need greater mobility and on-demand availability of travel options and hence may be open to exploring the new alternatives.

TABLE 2 Results of the IPT Consideration and Ridehailing Adoption Model Components

Variables	**Joint model Ridehailing frequency: (base: none)** Coeff.	t-stat
Activity characteristics		
Makes unplanned trips	0.234	1.59**
Makes social trips usually by personal vehicle	0.313	1.54**
Undertakes shopping trips: Frequently without using personal vehicle or infrequently using personal vehicle	0.238	1.35*
Work characteristics		
Employer provides travel allowance	0.410	2.43
Distance to work*considered ridehailing for non-work only	-0.029	-2.49
Work duration in hours*departs before or after morning peak (8:00-11:00am)*considered ridehailing for non-work only	0.081	2.82
Work duration in hours*departs from home between 8:01-11:00am	0.067	3.16
Travels by public transport and faces penalty for late arrival	0.925	2.87
Personal vehicle ownership and use		
Uses personal vehicle for work * perceives lack of productive time use while driving * consideres ridehailing for work	0.313	*1.08*
Faces high stress and tension while traveling in two-wheeler	0.453	2.62
Attributes of other modes		
Monthly expense on auto-rickshaw (in Rs. 100)	0.034	4.88
Travel by IPT and finds bus reliability to be low	0.620	1.72
Difference in average journey time from home to work between public transport and personal vehicle	0.005	1.85
Considers three or more motorized modes for work	-0.331	-2.23
Socio-demographic characteristics		
Income > Rs. 20,000 * education UG and above	0.640	3.85
Spouse working*consideres ridehailing for work	0.310	1.62**
Perception of modal rating is unavailable	0.645	2.49
Thresholds		
Threshold 1 | 2	1.746	4.64
Threshold 2 | 3	2.627	6.67
Threshold 3 | 4	3.140	8.00

'*' represents variables significant at 85% one-sided, '**' for 90% one sided, italicized t-stat are insignificant at 85% one-sided, all other variables are significant at 95% one-sided, 'n/a' = not applicable

Intensity of Use of Ridehailing Services

The results of ridehailing frequency component from the joint model is presented in **Table 2**. A comparison of the difference in thresholds between consecutive levels of frequency decreases suggests that the propensity for more frequent trips by ridehailing increases once the initial inertia to adopt ridehailing services is overcome.

While numerous studies have analyzed the trip purposes for which ridehailing is often used, the interaction between activity characteristics and conventional mode attributes on intensity of ridehailing use has not been sufficiently explored. Workers who make social trips where the usual mode for such trips is personal vehicle exhibited a greater frequency of ridehailing trips. This indicates the potential for ridehailing to substitute personal vehicle trips for at least some discretionary purposes which may involve group travel.

Workers who make high frequency shopping trips using personal vehicle also had a greater tendency to use ridehailing services more frequently which may be motivated by avoiding parking cost or driving stress than less frequent shoppers with personal vehicles. Surprisingly, workers who participate less frequently in shopping activities and use non-personal vehicle modes as the main means of travel to these destinations were also more frequent users of ridehailing services. Thus, there is also some evidence of shift away from public transport or intermediate public transport modes albeit for different reasons that may include comfort and convenience.

Workers who make sudden or unplanned trips are likely to use ridehailing more frequently as these services are available on-demand and relatively low waiting times.

Perceived attributes of personal vehicle: Workers who reportedly face stress and tension while traveling in two-wheeler have a greater propensity to use ridehailing services more frequently. However, this shift from two-wheeler segment to car (or sometimes auto) in ridehailing is more likely during congested periods, but ironically can contribute further to congestion because of the shift to larger vehicle types (car, autos) unless such a shift to ridehailing occurs towards shared rides rather than solo trips.

Attributes of conventional IPT, in particularly, auto-rickshaws are key determinants of ridehailing frequency suggesting shared observed and unobserved factors influencing both modes. Workers who spend more on auto-rickshaws were also more frequent users of ridehailing, which is also consistent at the adoption level for these modes. Whether this represents a lateral shift from existing auto-rickshaws to ridehailing auto-rickshaws that operate at same cost due to better operational characteristics, or represents an upgrade in comfort and convenience to cab services albeit at a higher cost is not clear because of the lack of data about frequency by ridehailing vehicle type. However, it has implications for possibly distinct market segments within ridehailing with very different willingness to pay for different service features.

Workers who usually travel by IPT and feel that the reliability of reaching the destination on time by bus is low tend to use ridehailing services more frequently. This suggests that IPT users are probably more sensitive to uncertainty in travel time and possibly be willing to use ridehailing services in case of any unexpected delay while traveling.

Workers who used three or more motorized modes for work trip during the last three months (other than ridehailing mode) use ridehailing services less frequently than other users. Thus, ridehailing only fulfills a gap when sufficient number of alternative modes are either unavailable or not preferred.

Among the level of service characteristics, as the difference between the average total journey time from home to work by public transport and personal vehicle increases, the intensity of using ridehailing services increases. Thus, ridehailing could draw shares from public transport on routes with low speeds and unreliable travel times. Longer work distances increases the propensity to chain non-work activities along work commute which is difficult to perform using ridehailing services.

It is to be noted that some of individuals were not asked about perceptions of modal ratings. A dummy variable indicating these individuals have been added to avoid any bias in estimating the parameters.

The results from the model shows the influence of some unique workplace characteristics (allowance for travel, penalty for late arrival etc.) on ridehailing frequency. Workers for whom the employer provides travel allowance tend use ridehailing more frequently as it enhances the affordability of using these services. Workers who travel by public transport and are subjected to penalty if they arrive late to the workplace are more likely to use ridehailing services frequently. Ridehailing may be used to reduce travel time or waiting delay in the access or line-haul portions of public transport trips.

Departure timings and work duration also influence ridehailing frequency. As work duration increases, individuals departing during the A.M. peak period were more frequent users of ridehailing. This is also consistent with driving stress avoidance noted in two-wheelers and unreliability of buses noted earlier. On the other hand, among users who depart during off-peak hours, the intensity of usage of ridehailing services exclusively for non-work purposes increases with increasing work duration. These may be the result of lower frequency of alternative non-personal vehicle modes. Thus, ridehailing may gain at the expense of other modes during peak and off-peak hours but for different reasons.

CONCLUSIONS

This study investigates the interrelationship between the three choice dimensions app-based ridehailing adoption, frequency of ridehailing trips and consideration of IPT services using data from a sample of workers in Chennai city, India. A trivariate probit model is estimated and used to testing the presence of endogeneity among these dimensions.

The results show that some factors influence only RH adoption and others only the intensity. Factors such as residential and work location, vehicle ownership, and availability of other modes affect ridehailing adoption while activity characteristics (purpose, duration and timing) and perception of conventional modes influence the intensity of use. There also common factors affecting both decisions. Thus, it is necessary to separate out factors regarding who uses RH from those which explain how much they use it. The results indicate no evidence of selectivity at the unobserved level, though common systematic influences are noted (e.g. income, IPT expenditure).

On the other hand, significant endogeneity is seen between consideration of IPT and adoption of RH at both systematic and error correlation levels. Higher income respondents and those who are more time-sensitive were more likely to consider both IPT and ridehailing options. Specifically, the use of IPT modes for commute, and non-compliance with regulated auto-rickshaw fares are consisent with greater adoption and usage levels of ridehailing modes.

The intensity of shopping trips and the choice of mode for these trips, work-related temporal constraints such as departure time to work, penalty for late arrival and work duration have significant effects on both IPT and ridehailing usage frequency. Other contextual variables (such as visits to unfamiliar destinations, travelling at odd times and carrying heavy luggage) contribute to higher ridehailing adoption and usage intensities. Interactions between modes considered for work commute and their attributes such as travel time reliability, the stress of travel and fare transparency influence both the ridehailing choice dimensions. Further, the availability of or access to transit modes and their use for work trips influence ridehailing adoption.

This study has brought to light some findings that contrast with existing literature such as significant interaction between ridehailing adoption and the consideration propensity of IPT modes. Second, significant difference is seen in RH adoption and frequency between two-wheeler and car owning segments through their valuation of different service attributes. Thirdly, the significant role of work-related spatial and temporal characteristics on the adoption and usage intensity of ridehailing services of workers in the developing country context is highlighted.

The study examines the ridehailing adoption and intensity among workers. The usage among other segments remains an important direction for further study. Comparison of behaviours across other cities in India, and other developing countries in the future could be useful to benchmark the evolution of these services across geographies. Modeling the intensity of ridehailing together with those of other conventional IPT modes is yet another direction to enable quantification of modal shifts to RH.

ACKNOWLEDGMENTS

The authors acknowledge the opportunity provided by the Government of India (GoI) under the Scheme for Promotion of Academic and Rsearch Collaboration (SPARC) in facilitating this research collaboration across various academic institutions. This work is also partly supported through the Centre of Excellence in Urban Transport (CoEUT) at IIT Madras, funded by the MoUD, GoI. Their support is gratefully acknowledged.

AUTHOR CONTRIBUTIONS

The authors confirm contribution to the paper as follows:
Study Conception and Design: Aravinda Devaraj, Ganesh AmbiRamakrishnan, GopindraSivakumar Nair, Karthik K. Srinivasan, Chandra R. Bhat, Abdul R. Pinjari, GitakrishnanRamadurai and Ram M. Pendyala
Data collection: Aravinda Devaraj, Ganesh AmbiRamakrishnan, Karthik K. Srinivasan and GitakrishnanRamadurai, Abdul R. Pinjari
Analysis and interpretation: Aravinda Devaraj, Ganesh AmbiRamakrishnan, GopindraSivakumar Nair, Karthik K Srinivasan, Abdul R. Pinjari, Chandra R. Bhat, Ram M. Pendyala
Draft manuscript preparation: Aravinda Devaraj, Ganesh AmbiRamakrishnan and Karthik K. Srinivasan, Chandra R. Bhat, Ram M. Pendyala
All authors reviewed the results and approved the final version of the manuscript.

REFERENCES

1. Vinayak, P., F. F. Dias, S. Astroza, C. R. Bhat, R. M. Pendyala, and V. M. Garikapati. Accounting for Multi-Dimensional Dependencies among Decision-Makers within a Generalized Model Framework: An Application to Understanding Shared Mobility Service Usage Levels. *Transport Policy*, Vol. 72, No. September 2017, 2018, pp. 129–137. https://doi.org/10.1016/j.tranpol.2018.09.013.
2. Lavieri, P. S., and C. R. Bhat. Investigating Objective and Subjective Factors Influencing the Adoption , Frequency , and Characteristics of Ride-Hailing Trips. *Transportation Research Part C*, Vol. 105, No. May 2018, 2019, pp. 100–125. https://doi.org/10.1016/j.trc.2019.05.037.
3. Dias, F. F., P. S. Lavieri, V. M. Garikapati, S. Astroza, R. M. Pendyala, and C. R. Bhat. A Behavioral Choice Model of the Use of Car-Sharing and Ride-Sourcing Services. *Transportation*, Vol. 44, No. 6, 2017, pp. 1307–1323. https://doi.org/10.1007/s11116-017-9797-8.
4. Feigon, S., and C. Murphy. *Shared Mobility and the Transformation of Public Transit*. Chicago, IL, 2016.
5. Sikder, S. Who Uses Ride-Hailing Services in the United States ? 2019. https://doi.org/10.1177/0361198119859302.
6. Habib, K. N. 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. No. January, 2019.
7. Xie, Y., M. Danaf, C. Lima, A. Arun, and P. Akkinepally. Behavioral Modeling of on Demand Mobility Services : General Framework and Application to Sustainable Travel Incentives. No. 0123456789, 2019.
8. Alemi, F., G. Circella, P. Mokhtarian, and S. Handy. What Drives the Use of Ridehailing in California ? Ordered Probit Models of the Usage Frequency of Uber and Lyft. Vol. 102, No. May 2018, 2019, pp. 233–248. https://doi.org/10.1016/j.trc.2018.12.016.
9. World Economic Forum. *Reshaping Urban Mobility with Autonomous Vehicles Lessons from the City of Boston*. 2018.
10. Cervero, R., A. Golub, and E. E. Publishers. Informal Public Transport: A Global Perspective. No. January 2011, 2011, pp. 488–518.
11. Kunhikrishnan, P., and K. K. Srinivasan. Investigating Behavioral Differences in the Choice of Distinct Intermediate Public Transport (IPT) Modes for Work Trips in Chennai City. *Transport Policy*, Vol. 61, No. November 2017, 2018, pp. 111–122. https://doi.org/10.1016/j.tranpol.2017.10.006.
12. Mani, A., M. Pai, and R. Aggarwal. Sustainable Urban Transport in India.
13. Garg, S., A. S. Gayen, P. Jena, G. S. Joe, L. Ramamurthy, J. K. M, and D. Dhanuraj. *Study on the Autorickshaw Sector in Chennai*. Chennai, 2010.
14. Toshniwal, R., and A. Mani. Assessing the Impact of Auto-Rickshaw Fare Reforms in Chennai Background Key Statistics on Auto-Rickshaws in Chennai. No. April, 2014.
15. Toshniwal, B. R. Can Auto-Rickshaw Fare Reform in Chennai Lead Users to Choose Sustainable Transport ? No. April 2014, 2018, pp. 9–10.
16. Prabhu, A., M. S, L. Ramamurthy, and D. Dhanuraj. *Study on Paratransit Sector in Chennai*. 2011.
17. Basu, R., V. Varghese, and A. Jana. Comparison of Traditional and Emerging Paratransit Services in Indian Metropolises with Dissimilar Service Delivery Structures. *Asian Transport Studies*, Vol. 4, No. 3, 2017, pp. 518–535.
18. Alemi, F., G. Circella, P. Mokhtarian, and S. Handy. Exploring the Latent Constructs behind the Use of Ridehailing in California. *Journal of Choice Modelling*, Vol. 29, No. July, 2018, pp. 47–62. https://doi.org/10.1016/j.jocm.2018.08.003.
19. Rayle, L., D. Dai, N. Chan, R. Cervero, and S. Shaheen. Just a Better Taxi? A Survey-Based Comparison of Taxis, Transit, and Ridesourcing Services in San Francisco. *Transport Policy*, Vol. 45, 2016. https://doi.org/10.1016/j.tranpol.2015.10.004.

20. Clewlow, R. R., and G. S. Mishra. *Disruptive Transportation: The Adoption, Utilization, and Impacts of Ride-Hailing in the United States*. 2017.
21. Young, M., and S. Farber. The Who, Why, and When of Uber and Other Ride-Hailing Trips : An Examination of a Large Sample Household Travel Survey. *Transportation Research Part A*, Vol. 119, No. June 2018, 2019, pp. 383–392. https://doi.org/10.1016/j.tra.2018.11.018.
22. Wilbur Smith Associates Private Limited. *Chennai Comprehensive Transportation Study - 2007*. Chennai, 2010.