Exploring ride-hailing mode preferences -a stated choice study considering social and spatial proximities and attitudes

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SHORT SUMMARY

This study investigates individuals' choices among app-based ride-hailing modes auto-rickshaws, and conventional and electric four-wheeled taxis prevailing in Indian cities. Using a stated choice experiment conducted in urban workplaces in Hyderabad, India, the study incorporates spatial and social proximity measures, as well as environmental and technology attitudes, to analyze preferences among different ride-hailing modes. This study develops an ego-involvement index to assess proximity effects. Results reveal that spatial and social proximity significantly influence electric taxi use, with spatial proximity having a stronger impact. Also, individuals maintaining pro-technology and pro-environmental attitudes, 'Gen Zs', females, and high-income respondents prefer electric taxis over conventional taxis. Tailpipe emissions negatively affect auto-rickshaw preferences, with users willing to pay ₹6.28 per gm/km to reduce emission from the mode. Respondents are willing to pay an additional ₹172.0 to save one hour of in-vehicle time, ₹4.10 per unit increase in customer reviews for electric taxis. Findings emphasize targeted interventions for electric ride-hailing.

Keywords: Auto rikshaws, Stated Choice, EI-Index, Electric taxis, Ride-hailing.

1. INTRODUCTION

Ride-hailing services, significantly contribute to the urban mobility in India. These services, accessed through smartphone applications, offer users a flexible, on-demand alternative to traditional transportation modes. Ride-hailing platforms have been widely adopted in cities globally due to their convenience, affordability, and ability to meet diverse travel needs (Tirachini, 2020). However, these services have raised several challenges, including increased vehicle miles travelled, congestion, and adverse impacts on transit (Wang et al., 2022; Das, 2020). The absence of ride-hailing options during driver strikes in Indian cities reduced travel times by 10% to 14% in congested areas (Agarwal et al., 2023). On the other hand, ride-hailing options reduced vehicle ownership by 7.7% in several Indian cities (Wadud and Namala, 2022). Understanding consumer preferences among different ride-hailing modes can be beneficial to mitigating negative externalities such as air pollution and understanding the demand for sustainable ride-hailing options. This study contributes to understanding choices among ride-hailing options.
Previous studies have identified age, gender, income, waiting time, and travel cost to be significant determinants of ride-hailing services (RHS) (Bhaduri et al., 2022; Gomez, 2021; Young and Farber 2019). Younger adults are more likely to adopt RHS due to their affinity to adopt newer technology (Gomez, 2021; Young and Farber, 2019). Positive word of mouth from close social networks, such as family and friends, fosters a favourable attitude toward RHS (Goel and Haldar, 2020). Also, collective societal attitudes and peer validation significantly impact an individual's decision to adopt RHS (Bhaduri and Goswami, 2023). Social influence impacts individuals' preferences at various levels. For instance, spatial proximity plays a significant role, as individuals residing in densely populated urban areas exhibit a higher propensity for RHS (Dean and

Kockelman, 2021, Mondal and Bhat, 2021). This correlation can be attributed to built environment features, the availability of RHS services, and latent behavioural tendencies shaped by social learning. Similarly, social proximity, the influence of social network members on an individuals' travel options is also relevant. For example, shared experiences and discussions among workplace colleagues significantly shape preferences for shared mobility, including RHS (Goel and Haldar, 2020). This highlights that social learning influences individuals at both residential and workplace locations. Social network analysis suggets that individuals with strong ego-networks and spatial neighborhoods are likely to adopt similar travel modes (Pike, 2014; Bhaduri et al., 2024).

While the literature examines how individuals choose between conventional transportation modes and RHS, a knowledge gap exists on understanding preferences among different mode options in ride-hailing, such as three-wheeled auto-rickshaws, and four-wheeled conventional and electric taxis, , which are prevalent in many developing economies. This study addresses this gap by investigating preferences for these RHS options, which represent major RHS modes in India. India has the major share (75%) of the world's auto-rickshaws (Das et al., 2023). Conventional four-wheeled taxis are a major service mode for app-based RHS in India, and recently, service providers, such as Uber and BlueSmart, have begun integrating electric four-wheeler fleets into their operations. Understanding preferences among these RHS options provides valuable insights for promoting sustainable mobility, and design interventions that encourage the use of eco-friendly transportation options, such as electric taxis. Another significant gap in the existing literature is related to spatial and social proximity measures. Current studies predominantly rely on the proportion of alters in a social network and neighborhood members within the residential location (Walker et al., 2011; Pike, 2014) as indicators of social connections. However, this approach fails to adequately account for the impact of dissimilar choices. To address this, we have developed a modified external-internal index, inspired by social network analysis (Krackhardt and Stern, 1988). Further, previous studies have explored the effects of environmental attitudes and technological affinity on preferences for ride hailing among conventional RHS, public transit, and private vehicles, without explicitly considering electric taxis (Etminani-Ghasrodashti and Hamidi, 2019; Frei et al., 2017).

Based on the above, the objectives of the paper are: (1) Investigating the influence of spatial proximity (residential census-ward) and social proximity (workplace social connections) on different RHS options. (2) Assessing the impacts of latent attitudes on RHS options. With the growing emphasis on electrification in urban mobility, understanding preferences for electric taxis compared to conventional fuel ride-hailing options such as auto-rickshaws and conventional taxis is relevant. Using a stated choice survey and econometric modeling, this paper investigates ride-hailing modes, including three-wheeled auto-rickshaws (AR), four-wheeled conventional taxis (CT), and four-wheeled electric taxis (ET).

2. DATA COLLECTION AND ANALYSIS

The stated choice (SC) experiment elicited preferences among app-based RHS, including AR, CT, and ET. The experiment includes (Table 1) five key attributes identified through an extensive literature review. The selected service attributes include fixed fare, waiting time, in-vehicle travel time, tailpipe emissions, and customer reviews. The attribute levels for fixed fare, waiting time, and in-vehicle travel time were derived from ride-hailing user data and real-time data collected from prominent app-based platforms in the study area.

The SC scenarios were designed using an orthogonal experimental design implemented in Ngene. Three blocks were designed, each containing six scenarios. These attributes and levels collectively captured the trade-offs consumers face when choosing among ride-hailing options (Table 1). The survey was conducted in Hyderabad (Figure 1), a metropolitan city in India known for its diverse job sectors. To implement the survey, a team of six trained enumerators coordinated with workplace managers to engage employees during meal breaks. The survey also captured socio-demographic data and detailed information on respondents' workplace members.

Table 1: Attributes and Levels

Attributes		Auto Rikshaw	Conventional Taxi	Electric Taxi
Waiting time (in minutes)		5/5 to 15/>15	5/5 to 15/>15	30/30 to 60/>60
Tailpipe emissions (gm/km)		20/60/120	90/150/250	0
Customer Reviews (stars)		2/4.5	2/4.5	2/4.5
Fixed Fare (in Rupees)	Short trip (5 km)	80/140/200	140/220/300	140/180/220
	Medium trip (10 km)	120/190/260	200/400/600	190/240/290
	Long trip (15 km)	260/310/360	380/520/660	280/330/380
In-vehicle travel time (in minutes)	Short trip (5 km)	10/16/25	10/15/20	15/20/25
	Medium trip (10 km)	25/30/35	15/25/35	20/30/45
	Long trip (15 km)	35/40/45	25/40/55	25/40/60

Respondents were asked to list a maximum of 10 colleagues (alters) with whom they interact frequently. These ego-alter networks provided insights into workplace social connections. Furthermore, the survey included 12 attitudinal statements to capture respondents' environmental and technological opinions on a 5-point Likert scale (Table 2). The data collection was conducted in two phases, from November 2023 to June 2024, across 104 workplaces in Hyderabad. The survey collected 1,289 responses with 1,062 useable records. The respondents' home and work locations were also captured (Figure 1). An average respondent is 28 years old. Females comprised 33.71% of the respondents, and 11.1% of the sample earn over 1 million rupees annually. Notably, 58.76% of the sample include individuals born after 1996 (Gen Z). Regarding workplace distribution, the sample included 42.65% blue-collar workers, 46.70% white-collar workers, and 10.64% pink-collar workers. On average, each respondent named 6 individuals in their workplace network.

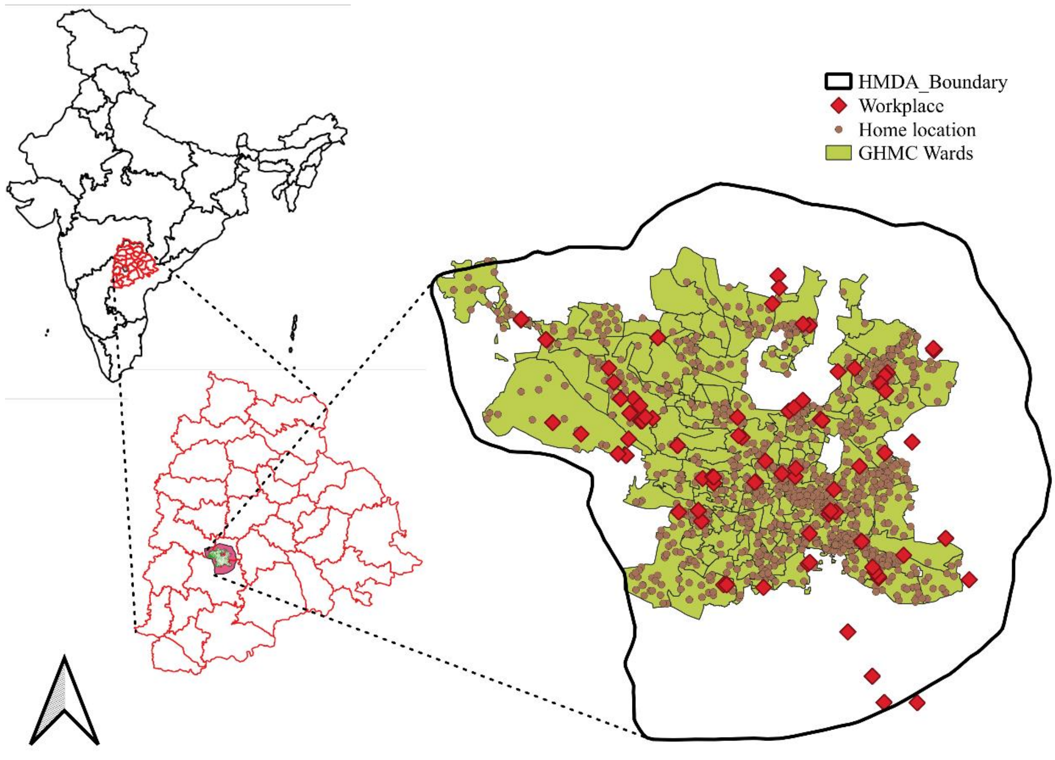

Figure 1: Greater Hyderabad Municipal Corporation Area

3. METHODOLOGY

To examine the influence of spatial and social proximity, we defined individuals' influence by both those who live within their residential location and by their colleagues at workplaces. Spatial proximity was determined using residential-ward, while social proximity was assessed using ego-alter network information. To quantify these proximities, we employed the Ego-Involvement Index (EI-Index[1]), also known as the External-Internal Index (Krackhardt and Stern, 1988; Maness, 2015). The EI-Index (Eqn.1), calculates the proportion of similar choices among an individual's network while subtracting the proportion of dissimilar choices, making it a more realistic measure than simply using the proportion of similar choices. For spatial proximity, the EI-Index was calculated by categorizing individuals within the same census ward as either "similar alters", if they shared the same ride-hailing preferences or "dissimilar alters", if their preferences different. For social proximity, the EI-Index was calculated using ego-alter workplace networks. Egos listed their colleagues, alters who chose the same mode as the ego were categorized as "similar alters," while those choosing a different mode were labelled "dissimilar alters."

$$EI - Index = \frac{X_{n(i\rightarrow i)} - (F_{nj}X_{n(i\rightarrow j)} + F_{nk}X_{n(i\rightarrow k)})}{X_{n(i\rightarrow i)} + (F_{nj}X_{n(i\rightarrow j)} + F_{nk}X_{n(i\rightarrow k)})} \quad (1)$$

$X_{n(i\rightarrow i)}$ is number of alters within the ego "n"s network who chosen the similar choice "i"
$X_{n(i\rightarrow j)}$, $X_{n(i\rightarrow k)}$ is number of alters in the ego "n"s network who chosen a different choice "j" and "k", respectively.
F_{nj}, and F_{nk} are proportions of dissimilar choices of alters of dissimilar choices "j" and "k", respectively

Table 2: Attitudinal statements

SN	Statement	Mean	Std.D
ST1	I generally talk about new technologies with my friends	1.124	0.991
ST2	I do not consider the impact of my actions on the environment when I make decisions (reversed)	0.120	1.333
ST3	I generally buy new technology products	0.705	1.153
ST4	I believe that current environmental protections are insufficient	0.891	1.096
ST5	It is important for me to follow technological development.	0.914	0.952
ST6	I don't think electric vehicles are a great option for short commutes and urban driving. (reversed)	0.142	1.245
ST7	I am not willing to bear some inconveniences for the sake of the environment. (reversed)	0.069	1.261
ST8	Science and technology make our lives easier and more comfortable	0.907	1.109
ST9	I believe technology should be used more responsibly to reduce our reliance on non-renewable resources.	0.855	1.149
ST10	I do not worry about environmental destruction and the waste of natural resources. (reversed)	- 0.087	1.315
ST11	Scientific and technological developments can have unforeseen side effects that are harmful to human health and the environment. (reversed)	0.140	1.362
ST12	The applications of science and new technologies will make people's work more interesting	1.014	1.049

For spatial proximity, the average EI-index is observed as 0.005, with a standard deviation of 0.251, indicating that the spatial proximity in most wards is relatively balanced with a tendency towards homophily. Regarding, social proximity, the average EI-index is 0.057, with a standard deviation of 0.336, suggesting a slight tendency towards homophily in the workplace social networks.

[1] +1: pure homophily, all preferences alters within the network or census ward are similar; -1: pure heterophily, all preferences of alters are dissimilar to the ego

Exploratory Factor Analysis (EFA) on 12 attitudinal-based questions identified three latent factors (KMO>0.850; Table 2). The Confirmatory Factor Analysis (CFA) was revealed 11 out of 12 measurement items were statistically significant (Table 3). Four items were loaded onto the "Pro-Technology" construct, four onto the "Environmental Concern and Technology" construct, and three onto the "Pro-Environment" construct.

Table 3: Confirmatory Factor Analysis results

Factor name (Notation)	Statement No	Estimate	Standard Error	P-value
Pro Technology (Pro_Tech)	ST10	0.708	0.056	***
	ST3	0.733	0.051	***
	ST11	1		
	ST1	0.598	0.043	***
Technology & Environment concern (Pro_TE)	ST12	0.887	0.068	***
	ST9	0.905	0.073	***
	ST4	1		
	ST5	0.723	0.06	***
Pro Environmental (Pro_Env)	ST6	1		
	ST2	0.971	0.068	***
	ST7	0.767	0.062	***

*** = Significant with 99% confidence level

Indices Type	Recommended Value	Observed Value
RMSEA (Root Mean Square Error Approximation)	<0.08	0.058
IFI (Incremental Fit Index)	>0.90	0.944
CFI (Comparative Fit Index)	>0.90	0.944
TLI (Tucker-Lewis Index)	>0.90	0.92

4. RESULTS AND DISCUSSIONS

We estimated[2] a Multinomial Logit model incorporating spatial and social proximity measures using the EI-index, with corrections for endogeneity in the social proximity variable, as it involves proportions derived from dependent variables. No significant endogeneity was observed for spatial proximity, allowing it to be included in the model without any correction (Table 4).

Gen Zs shows a higher preference for conventional taxis (CT) and electric taxis (ET), aligning with the previous findings (Bhaduri and Goswami, 2023). This study extends that understanding by showing that within RHS, Gen Z generally favours CTs over ETs. Furthermore, females show a significant preference for ETs over CTs. Higher-income individuals, earning more than 2 million rupees annually, exhibit a strong preference for ETs and CTs, with ETs being preferred over CTs. Regarding service attributes, fixed fare negatively impacts all modes, with shares of ETs being the most sensitive. Waiting time has a significant negative effect on both ARs and CTs, with the utility of CTs exhibiting greater sensitivity, underscoring the expectation of convenience and minimal delays in taxis. Similarly, in-vehicle travel time negatively affects preferences across

[2] We also estimated a mixed multinomial logit (MMNL) model allowing for panel heterogeneity/state dependance but found limited statistical evidence to justify their use.

all RHS, with the strongest effect on CTs. Although ETs are also negatively impacted by in-vehicle travel time, the effect is insignificant. Tailpipe emissions significantly influence preferences for ARs, with a strong negative effect, reflecting users' awareness of environmental impacts in choosing three-wheeled modes. However, this effect is not significant for CTs. Customer reviews play a critical role in all modes. CTs are the most influenced by customer reviews, followed by ARs and ETs, highlighting the importance of social validation and perceived service quality, especially for CTs, where these attributes drive user trust and satisfaction.

Table 4: MNL Model Estimates

	MODEL 2 (Corrected endogeneity for social proximity)					
Attribute	**AR**		**CT**		**ET**	
	Estimate	t-Stat	Estimate	t-Stat	Estimate	t-Stat
ASC			-5.764***	-9.107	-7.649***	-9.475
Age (Genz)			0.145**	2.173	0.111	1.61
Income (>2 million rupees)			0.838**	2.496	0.707**	2.088
Female			0.100	1.39	0.23***	3.139
Fixed fare	-0.347***	-3.423	-0.231	-1.633	-0.699***	-3.97
Waiting time	-0.16**	-2.242	-0.191**	2.365	-0.004	0.029
In-vehicle travel time	-0.035	-0.297	-0.534***	-5.971	-0.221*	-1.88
Tailpipe emissions	-0.052	-1.34	0.001	0.002		
Customer reviews	0.317***	4.687	0.598***	9.449	0.155**	2.559
White collar employees			-0.754***	-6.322	0.066	0.493
Blue collar employees			-0.491***	-4.5	-0.152	-1.196
Pro-Tech			0.013	0.825	0.047***	2.924
Pro-Env			-0.062***	-4.228	0.046***	3.023
Spatial proximity			1.66***	16.433	2.362***	21.574
Social proximity			1.405**	2.142	1.61**	2.454
Social proximity residuals			1.208*	1.851	1.208*	1.851
No.of individuals/observations	1062/6372					
Initial log likelihood	-7000.36					
Log likelihood at convergence	-6206.41					
AIC	12482.82					
BIC	12719.41					
Adj.Rho-squared	0.103					
***: p<0.01, **: p<0.05, *: p<0.10, AR: Auto Rikshaw, CT: Conventional Taxi, ET: Electric Taxi						

Regarding job-type, white-collar employees exhibit a negative preference for CTs. In contrast, their preference for ETs is positive, though not statistically significant, indicating a moderate inclination toward sustainable mobility options. Blue-collar employees also demonstrate a significant negative preference for CTs, though the magnitude of this effect is smaller compared to white-collar employees. This suggests that job roles involving more technical or formal work environments are less likely to favour CTs, potentially aligning with sustainability values. Individuals with pro-technology attitudes exhibit a significant positive preference for ETs compared to CTs, emphasizing the perception of ETs as technologically advanced mobility options. Similarly, individuals with pro-environmental attitudes demonstrate a significant positive preference for ETs while showing a significant negative preference for CTs. The strong preference for ETs among environmentally conscious individuals highlights their alignment with sustainable

transport options, as ETs produce zero tailpipe emissions and are often promoted as a greener alternative.
Regarding spatial proximity, the presence of homophily within census wards shows a positive effect on RHS choices, particularly for ETs. This suggests that the use of RHS is significantly influenced by spatial proximity, which encourage individuals within the same geographic area to choose similar modes. Regarding social proximity, homophily within workplace networks exhibits a strong positive influence on RHS preferences, particularly for ETs. Individuals are more likely to adopt ETs when they observe their colleagues preferring them. This highlights the role of workplace members in fostering positive perceptions of ETs, as peer endorsements and feedback within these networks can encourage individuals to consider adopting sustainable travel modes. Overall spatial proximity is more impactful than social proximity on the likelihood of choosing ETs.
We estimated the Willingness to Pay (WTP) for several attributes, using t-tests and confidence intervals (Monte Carlo simulations with 1,000 draws). Respondents are willing to pay 172 rupees extra per hour saved for in-vehicle travel time in ETs, emphasizing the importance of time savings in consumer preferences. Whereas for CTs, individuals are willing to pay only 14 rupees to save one hour. Individuals are willing to pay a higher premium for modes with good customer reviews. For ETs (₹4.10/unit), compared to ARs (₹1.00/unit) and CTs (₹0.21/unit). This could be due to ARs and CTs, which are more established modes of transport, where respondents may already have formed strong perceptions and rely less on external validation through reviews. Consumers are willing to pay ₹6.28 more per gm/km decrease in tailpipe emissions for ARs, indicating a strong preference for lower emissions.

5. CONCLUSIONS

This study provides insights into preferences for ride-hailing mode options, such as auto-rickshaws, and conventional and electric taxis. The results emphasize the significant influence of spatial and social proximity, particularly in shaping preferences for electric taxis. Findings highlight the importance of promoting environmentally friendly and technologically advanced options, as individuals who are environmentally conscious, tech-savvy, Gen Z, females, and high-income individuals show a stronger inclination towards electric taxis. Tailpipe emissions from auto-rickshaws are a major deterrent, indicating the need for cleaner transportation solutions. These results provide insights into understanding of ride-hailing demand by mode options.

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