CHALMERS
UNIVERSITY OF TECHNOLOGY

Modeling commuters' preference towards sharing paratransit services

(article starts on next page)

Transport Policy 143 (2023) 132–149

Contents lists available at ScienceDirect

Transport Policy

journal homepage: www.elsevier.com/locate/tranpol

Modeling commuters' preference towards sharing paratransit services

Deepjyoti Das [a,b,*], Eeshan Bhaduri [c], Nagendra R. Velaga [d]

[a] Division of Environmental Systems Analysis (ESA), Department of Technology Management and Economics, Chalmers University of Technology, Gothenburg, 41258, Sweden

[b] Centre for Urban Science and Engineering (CUSE), Indian Institute of Technology Bombay, Powai, Mumbai, 400076, India

[c] Ranbir and Chitra Gupta School of Infrastructure Design and Management, Indian Institute of Technology Kharagpur, Kharagpur, 721302, India

[d] Transportation Systems Engineering, Department of Civil Engineering, Indian Institute of Technology Bombay, Powai, Mumbai, 400076, India

A R T I C L E I N F O

Keywords:
Stated preference
Mixed logit model
Willingness-to-Pay
Sustainability
Shared transportation
Developing nation

A B S T R A C T

The transportation sector in India faces significant issues, such as congestion and air pollution, and is in dire need of sustainable strategies. Sharing vehicles is one of the popular sustainable strategies. Sharing auto-rickshaws, a paratransit mode, currently informally operating with a significant mode share, offers an opportunity to tackle sustainability issues. There are several challenges to integrating and promoting auto-rickshaw system as shared transportation using a formal structure of policies. The primary reason is a dearth of studies on sharing auto-rickshaws, leading to policymakers lacking knowledge and focus. The present study contributes to the literature to divert focus on sharing auto-rickshaws in India, considering Mumbai Metropolitan Region (MMR) as a study area. This study attempts to assess and model the intentions of users and non-users toward auto-rickshaw sharing using stated preference (SP) choice experiments and estimate Willingness-to-Pay (WTP) considering multiple socio-economic heterogeneities. Results highlight that the most critical attributes are travel time reliability and access time among different groups. Importance of having real-time information on trips among females and sharing auto-rickshaw users is high. The study provides a transparent direction toward ensuring efficient and integrated policymaking and guidelines for promoting auto-rickshaw sharing in urban areas of the Indian subcontinent with limited resources.

1. Introduction

Globally, sustainability of the transportation sector is a major concern (Das et al., 2021a). Due to unsustainable air pollution, traffic congestion, and fuel consumption caused by private vehicles in cities, it is essential to improve public transit systems and develop other transportation options, accounting for those who do not have cars and depend on public transportation (PT). Traditional fixed PT routes with pre-determined stops may not address "first-mile" or "last-mile" journeys; paratransit or intermediate public transit (IPT) can potentially help in addressing the issue (Basu et al., 2017). Along similar lines, urban areas in the most populous nation in the world, i.e., India, also have PT with inadequate resources and capacity where IPT, like auto-rickshaws (refer to Fig. 1), a privately operated motorized mode, caters to the demand gap from PT for commuters (Das et al., 2022b; Das and Mandal, 2021; Konbattulwar et al., 2016; Santana Palacios et al., 2020; WPR, 2023). Unlike PT modes, auto-rickshaws provide door-to-door connectivity, and maneuverability is higher in dense urban areas due to their small size with low fares (Abu Mallouh et al., 2011; Harding et al., 2016; Nugroho et al., 2020). However, an unsustainable overall gap between demand and transportation infrastructural capacity to cater to the increased vehicle demand in India is leading to severe congestion, which is directly increasing pollution, health issues for commuters, accidents, loss of productive time, and fuel wastage (Bhaduri et al., 2020; Cheranchery and Maitra, 2021; Maitra et al., 2015). For example, an estimated congestion cost for a city like Delhi (in India) is 8.9 billion USD annually (Joseph et al., 2015). Building more transportation infrastructure to tackle city traffic congestion is always an option. However, considering a space crunch in dense Indian cities, there is an urgent need to decongest the city roads with an exemplary and immediate shift toward sustainable and smart transportation systems (Das et al., 2021a). Sharing vehicles is one of the most capable options to counter concerns affecting India's transportation sector's sustainability (Das et al., 2022a).

* Corresponding author. Division of Environmental Systems Analysis (ESA), Department of Technology Management and Economics, Chalmers University of Technology, Gothenburg, 41258, Sweden.

E-mail addresses: dasd@chalmers.se, das.deepj10@gmail.com (D. Das), eeshanbhaduri@iitkgp.ac.in (E. Bhaduri), n.r.velaga@iitb.ac.in (N.R. Velaga).

https://doi.org/10.1016/j.tranpol.2023.09.008
Received 26 February 2023; Accepted 8 September 2023
Available online 11 September 2023

Auto-rickshaws increase the share of PT by providing last-mile connectivity and decrease demand for private vehicles having high per capita emissions as an alternative to door-to-door connectivity. Almost 75 percent of global auto-rickshaws operate in India and have a significant share among motorized transportation modes ranging from 11 to 20 percent in different cities (Mani et al., 2012; Mani and Pant, 2012). Therefore, auto-rickshaws are a key component for the sustainability of India's passenger transportation. However, according to Das and Mandal (2021), in their present form, auto-rickshaws cannot be considered a sustainable way of travel because they primarily run on petrol or diesel, resulting in high emissions from the road transportation sector. CNG fleets and 4-stroke engines should be promoted, and ride-sharing should be encouraged to make them more eco-friendly (Gohil et al., 2020; Macarthur and McKinsey, 2015; Mani and Pant, 2012; Trivedi et al., 2020). In India, the conversion of auto-rickshaws to CNG and 4-strokes has been given significant attention; however, the promotion of ride-sharing in auto-rickshaws remains largely absent (Das and Mandal, 2021; Mani, 2010, 2012; Mani and Pant, 2012; Shlaes and Mani, 2014).

Auto-rickshaws have a permissible capacity of seating three adults and a driver (refer to Fig. 1) (Schmucker et al., 2011). As auto rickshaws can carry multiple passengers, they provide a favorable opportunity to operate as a sharing vehicle and promote Sharing Economy (SE). Auto-rickshaws in India travel empty on average 20% of their total travel kilometers (Rajkot, 2014), a significant setback to India's focus on reducing transportation sector emissions to fulfill the targets of 2015's Paris climate agreement. Promoting auto-rickshaw sharing among commuters provides an opportunity to reduce empty kilometers and overall emissions. Many studies have highlighted the importance of the emerging SE culture in India as a positive step toward sustainability (Panda et al., 2015). SE services such as Airbnb (Hospitality), Swiggy (Food and Beverage), and OlaShare (Transport) have received immense popularity in India (Biswas et al., 2015). Still, the availability and operation of sharing auto-rickshaws in India are limited, and there are few studies on auto-rickshaw sharing in India (Panda et al., 2015). There is a need in India to formulate policies, which can accelerate auto-rickshaw sharing (Das and Mandal, 2021), and the present study could be considered a small step toward diverting focus on auto-rickshaw sharing. Additionally, due to the dearth of knowledge and insufficient research on IPT modes in India, authorities perceive auto-rickshaws as unsafe and a reason for traffic congestion; therefore, auto-rickshaws receive significantly less focus than other modes during city planning (Kumar et al., 2016; Mani and Pant, 2012; Santana Palacios et al., 2020). Registration of new auto-rickshaws in the last three decades has been drastically increasing (Reddy et al., 2017). The trend may continue in the upcoming decades. Thus, there is an urgent requirement for studies on auto-rickshaw sharing, which can help policymakers promote auto-rickshaw sharing among commuters.

WTP has been used to promote policy development for alternative modes of transportation (Kraeusel and Möst, 2012). For instance, Basu and Hunt (2012) evaluated the attractiveness of sub-urban trains based on qualitative and quantitative attributes and showed the significance of WTP in addressing policy issues related to overcrowding. Similarly, Sadhukhan et al. (2016) employed WTP to formulate policies to improve transfer facilities near metro stations. Balakrishnan and Karuppanagounder (2021) also utilized WTP when analyzing policies concerning safe-route choices among motorized two-wheeler users, while Majumdar and Mitra (2019) estimated WTP values to create policies that would bolster bicycle infrastructure as a way to maintain existing users and attract new ones. To the author's knowledge, no study has yet attempted to understand the WTP of auto-rickshaw commuters to develop appropriate supporting facilities. Determining WTP values will provide valuable insight into potential benefits and additional charges that could reasonably be imposed on auto-rickshaw riders to finance improvements in their infrastructure and operations.

Further, Bera & Maitra (2022) suggested that users' socio-economic characteristics substantially influence their perceived benefits and choices towards a mode. Eldeeb and Mohamed (2022) and Sadhukhan et al. (2016) also recommended that understanding uniqueness in taste and attitude among different population classifications is essential for developing inclusive policies, where socio-economic and travel characteristics are the most popular classification of population. However, Gao et al. (2018) highlighted that most literature on different passenger transportation modes had limited their focus on estimating mean values of WTP and overlooked the preference heterogeneity caused by variations in cognitive biases and personal traits among commuters. Also, an understanding of heterogeneity among auto-rickshaw commuters is absent from the literature. Therefore, considering that metropolises in India have extensive socio-economic heterogeneity, understanding WTP changes corresponding to distinct socio-economic groups of auto-rickshaw commuters could assist in framing policy enhancements pertinent to an area concerning commuters' socio-economic background.

The present study is divided into two parts: firstly, SP survey data are collected and analyzed using the Mixed Logit (ML) model, and cognitive behavior of preferences among commuters is investigated; and secondly, WTPs of commuters belonging to distinct socio-economic groups are compared for viable improved facilities.

2. Literature review and research gap

For this study, a comprehensive literature analysis was conducted to evaluate mode choice and policy development in the transportation

Fig. 1. Auto-rickshaw in India (source: Author).

sector. An extensive discussion of the attributes and methodologies used by various studies is provided in the following paragraphs, with an overview summarized in Table 1.

Research conducted in different settings revealed that both quantitative and qualitative attributes of transportation services considerably impact commuters' decision-making process. The quantitative attributes such as fare, travel time, access time, waiting time, and transfers were among the most common attributes that related studies found to have a significant impact on commuter's mode choice preferences (Balakrishnan and Karuppanagounder, 2021; Bellizzi et al., 2020; Dandapat and Maitra, 2020; Eldeeb and Mohamed, 2022; Gao et al., 2018). Past related studies also pointed out qualitative attributes such as real-time information, vehicle characteristics, environmental awareness, crowding level, and driver's demographic characteristics, which influence commuter's perception during mode choice (Bellizzi et al., 2020; Dandapat and Maitra, 2020; Eldeeb and Mohamed, 2022; Gao et al., 2018; Jensen et al., 2021; Ma et al., 2019; Wisutwattanasak et al., 2022). Past studies are also divided based on their focus on single or multiple attributes for their assessment. For instance, the objective of Wang et al. (2018) was to improve the resilience attribute of New York's transportation system infrastructure. Ma et al. (2019) analyzed the impact of removing subsidies in promoting electric vehicles (EVs) in China by using segments of incentives as attributes. Beak et al. (2020) focused on the importance of an attribute representing environmental friendliness in attracting customers to purchase EVs. Similarly, price of service at different levels was utilized as an attribute by Fu et al. (2022) to understand choice of shared mobility with autonomous vehicles. In contrast, many studies utilized a combination of multiple attributes (Balakrishnan and Karuppanagounder, 2021; Bellizzi et al., 2020; Bera and Maitra, 2022; Dandapat and Maitra, 2020; Eldeeb and Mohamed,

Table 1
Summary of relevant literature on the estimation of WTP for policy development (last five years).

Study	Region	Data	Variables	Method	Focus	Heterogeneity
Bera & Maitra (2022)	Kolkata, India	SP	Price, public station, battery warranty, tailpipe emission, battery range, fuel cost reduction	MNL, ML	WTP for the attributes of Plug-in Hybrid Electric Vehicles (PHEVs)	Socio-demographic characteristics such as age, monthly family income, car ownership, home-based parking facility and education, and trip characteristics
Eldeeb and Mohamed (2022)	Hamilton, Canada	SP	Fare, Journey time, access time, transfers, service headway, real-time information	MNL, Random parameter logit (RPL)	WTP of transit service improvements	Socio-economic characteristics, transit usage, user type, and attitude
Fu et al. (2022)	Alabama, USA	SP	Price of service	Random parameter ordered logit	WTP for shared autonomous vehicle (SAV) services	Socio-demographic, awareness, and experience
Wisutwattanasak et al. (2022)	Thailand	Contingent valuation method (CVM)	Demographic characteristics	ML	WTP of driver attributes	Gender, attitude, annual mileage
Balakrishnan and Karuppanagounder (2021)	Kerala, India	SP	Travel time. Travel cost, crash rate	ML	WTP against crash reduction	Preference parameters
Jensen et al. (2021)	Denmark	SP	Cost, car characteristics, charging infrastructure	ML	WTP of PHEV characteristics and availability of charging infrastructure	Fuel type, car type
Beak et al. (2020)	South Korea	SP	Drive range, charging technology, charging time, autonomous driving function, CO_2 emissions reduction, price	ML	WTP of attributes of battery electric vehicles (BEVs)	Attributes of BEVs
Bellizzi et al. (2020)	Santander, Spain	SP	Waiting time, journey time, access time, level of occupancy, fare	Latent Class and Random Parameter ML models	WTP of service attributes	Socio-demographic, income, trip purpose, type of user
Dandapat and Maitra (2020)	Kolkata, India	SP	Type, waiting time, Comfort, Traffic information, Journey speed, Fare	RPL	WTP for improving bus service attributes	Socio-economic, trip, and demographic characteristics
González et al. (2019)	Teide National Park, Spain	SP	Parking cost, CO_2 emission, waiting time	ML	WTP for reducing waiting time and CO_2 emissions	Socio-economic characteristics
Ma et al. (2019)	China	SP	Driving range and charging attributes, reduction in EV operating costs, and EV-specific privileges.	MNL, ML	WTP for alternative incentives as subsidies	Socio-economic characteristics, vehicle type, city type, attitude
Majumdar and Mitra (2019)	Kharagpur and Asansol, India	SP	Road width, level of risk, route visibility, journey time, operating cost	RPL	WTP of bicycle infrastructure improvement	Trip purpose
Gao et al. (2018)	Shanghai, China	SP	Travel time, travel time unreliability, cost, crowding	RPL	WTP for travel-time reliability (TTR) improvement and in-vehicle crowding reduction	Socio-demographic, income
Giansoldati et al. (2018)	Friuli Venezia Giulia, Italy	SP	Price, driving range, operating cost, share of fast charging stations	Binary logit, ML	WTP of EV attribute improvements	Socio-economic characteristics
Wang et al. (2018)	New York, USA	SP	Improve operational transportation, WTP for resilience improvement	Mixed-mixed logit (MM-MNL)	WTP of improving resilience of transportation	Payment

2022; Jensen et al., 2021; Majumdar and Mitra, 2019).

Literature also highlights that estimation of WTP based on SP survey data has been a popular way of assessing different attributes for policy development of transportation infrastructure. For example, WTP for improving bus service (Dandapat and Maitra, 2020), bicycle infrastructure (Majumdar and Mitra, 2019), and travel-time reliability (TTR) with in-vehicle crowding (Gao et al., 2018) were assessed using Random parameter logit (RPL) on SP data from commuters. Similarly, many studies have used a combination of different models on SP data to estimate WTP, such as Eldeeb and Mohamed (2022), which employed Multinomial Logit (MNL) interaction models and an RPL model on SP data from consumers. The models were used to estimate WTP for understanding best investment decisions to improve transit service quality. Similarly, Giansoldati et al. (2018) utilized SP data from consumers of EV and petrol cars to develop binary logit and ML models. The models were used to estimate WTP of different EV attributes supporting the development of policies to influence consumers' purchasing decisions toward EVs. Studies such as Bera and Maitra (2022) and Ma et al. (2019) used a combination of MNL and ML models on SP data from commuters to estimate WTP changes on attributes of Plug-in Hybrid Electric Vehicles (PHEVs) and changing subsidies with incentives, respectively. However, most past studies used a single model to estimate WTP, and the most popular choice was the ML model. For example, Wang et al. (2018) utilized an ML model on SP data from residents of New York City to derive flexible distribution of WTP related to improving resilience of transportation infrastructure. Similarly, past studies estimated WTP of attributes to develop policies to reduce waiting time and CO_2 emission of shuttle buses in Spain (González et al., 2019), promote the adoption of Battery EVs (BEVs) and PHEVs (Beak et al., 2020; Bera and Maitra, 2022; Jensen et al., 2021) using ML model on SP data from consumers. Balakrishnan and Karuppanagounder (2021) and Wisutwattanasak et al. (2022) also developed ML models using SP data from commuters, where the models were used to estimate WTP for developing policies to reduce road accidents for two-wheelers and buses, respectively.

According to Balakrishnan and Karuppanagounder (2021), decision-making is sensitive to assumptions about preference heterogeneity, with taste homogeneity underestimating subjective values; therefore, accommodating preference heterogeneity in individual responsiveness improves model fit and reveals new information. Some related literature assessed variations in WTP values within population classes and highlighted that understanding taste heterogeneity among respondents is essential for efforts to develop sustainable policies for the transportation sector. For example, Gao et al. (2018) conducted a detailed study on understanding heterogeneity in valuation WTP changes for travel time reliability. The results indicated that variability in demographic attributes, spatial context, and time schedule are all found to influence preference heterogeneity for travel time reliability. The variation in WTP results based on education and income levels broaden the understanding of what affects WTP for travel time reliability, aiding in more accurate demand forecasting. Wisutwattanasak et al. (2022) conducted a detailed study on understanding car drivers' valuation of risk reduction measures for road accidents in Thailand. The results suggested that variables reflecting households with children, driving to work or for work, drivers' intention, and those with elderly were initially insignificant, but the heterogeneity modeling approach found them influential. The study highlights the importance of accounting for heterogeneities to uncover multi-layered effects of preference-level variables (e.g., demographic & psychological) on drivers' WTP for road safety, offering flexibility in WTP estimation. Majumdar and Mitra (2019) attempted to identify and evaluate significant attributes to help develop suitable policies to attract new bicycle users. The study concluded that valuation of factors is significantly influenced by trip purpose, which can be captured via heterogeneity investigation. The conclusion suggested that a single policy disregarding user needs and city characteristics would not suffice to improve bicycle infrastructure, with important implications for attracting choice users into bicycling. Throughout the literature, socio-demographic and trip characteristic variabilities were the most prevalently used in understanding heterogeneity of decision-making among commuters in mode choice (Bellizzi et al., 2020; Bera and Maitra, 2022; Dandapat and Maitra, 2020; Eldeeb and Mohamed, 2022; Fu et al., 2022; Giansoldati et al., 2018; González et al., 2019; Ma et al., 2019).

The use of auto-rickshaws as a form of paratransit has been largely studied in developing South Asian countries, such as India, from various perspectives. Nonetheless, paratransit services exist and are present in many other countries worldwide. The following subsections discuss global studies on how paratransit is being promoted across different nations, review multiple angles from which auto-rickshaw studies assess service quality in India, and identify key research gaps that need to be addressed.

2.1. Promoting paratransit services

Paratransit services are operated informally in emerging nations and offered by an individual who works as both driver and operator. Pandit and Sharma (2022) suggested a need to design future paratransit services that can improve drivers' earnings and working conditions and integrate information technologies. The improvement will enhance the overall services by paratransit which will be essential in increasing the adoption of paratransit services by commuters. Drivers of 'three-wheeler' paratransit services in the city of Kandy, Srilanka, reported that they would prefer access to social well-being schemes over improvement in work conditions and salary, whereas drivers in cities of Colombo and Moratuwa desired vice-versa (Kawasaki et al., 2019). Therefore, for a holistic improvement in satisfaction among drivers of paratransit, there is a need to enhance access to social well-being schemes, working conditions, and salary, which will translate into better driver behavior towards commuters. Paratransit service providers such as 'Tmpo' and 'Leguna' are significantly used by low-income workers, especially women in Dhaka, Bangladesh, and the primary problem faced by women in these paratransit modes is 'security and safety' (Rahman, 2022). The availability of real-time information can decrease 'security and safety' concerns in paratransit services. A flexible, inexpensive, and relatively comfortable paratransit mode is 'Amaphela', which operates in Cape Town, South Africa. Rink (2022) suggests that 'Amaphela' is treated as a threat to order by regional policymakers because of their informal operations; also, the informal structure increases safety and reliability issues for commuters. Weicker (2022) also pointed out that the paratransit mode in Russian cities is known as 'Marshrutkas', facing severe criticism and restrictions for being portrayed as unsafe, uncomfortable, supporting anti-social behavior, and tax evasion. There is a need to understand the importance of regional paratransit modes in the transportation system and support them to become formal, which can help increase acceptability and accountability, leading to safer and more reliable paratransit system development. 'Songtaew' is a paratransit mode operated in Khon Kaen City, Thailand. The survey results from Wongwiriya et al. (2020) showed that reliability and comfort strongly impact non-users decision of not to use Songtaew's service, whereas cheaper fares with convenient service are most important for present users to continue using the service. The study recommended that as fares of Songtaew are presently at an acceptable range, efforts should be concentrated on reducing the time spent traveling, including waiting and in-vehicle time, expanding its coverage areas, and prioritizing safety through monitoring driver behavior. The paratransit mode of 'Qingqi' is an essential part of the transportation system in Lahore, Pakistan, because of its flexibility and frequency. Javid et al. (2020) suggested that commuters are compelled to use Qingqi in high-density and low-to-middle-income areas because of a lack of access to bus services. The study highlighted that respondents opted out of using Qingqi services because of discomfort from overloading and music. Respondents who were users of Qingqi also viewed the mode as a major cause of traffic congestion. The study recommended that policymakers focus on regulating the informal structure by standardizing operations (i.e., schedule, fare structure, and routes) and driver's qualification, which will help ensure passengers' safety and security to make Qingqi acceptable to commuters. Johannes du Preez and Venter (2022) suggested that cities can conduct congestion studies and explore the possibility of effectively co-existing formal bus services with informal paratransit services in Tshwane, South Africa. The results support policy intervention of providing paratransit services access to dedicated bus lanes during peak periods of traffic, which could help promote paratransit services. Belgiawan et al. (2022) assessed the future of paratransit in Bandung, Indonesia. The study advised that paratransit services such as 'Jitneys' and 'Angkutan Kota in Indonesia and 'Tuk-tuk' in Thailand should be cautious not to substitute mass public transportation and should exist as feeder service providers. Campbell et al. (2019) highlighted that in Nairobi, Kenya, there is significant inequality in accessibility in different types of regions. There is a need to integrate land use policies with transportation policies, where flexible paratransit mode 'Matatus' can help provide safe, efficient, and affordable options for commuters. Matatus should be integrated with mass public and non-motorized transportation systems to increase its access and acceptability among commuters.

2.2. Studies on auto-rickshaw in India

Many studies have attempted to increase the efficiency of operations and adoption of auto-rickshaws (Devulapalli and Agrawal, 2017; Mani et al., 2012; Varghese and Jana, 2018). A study on auto-rickshaws in Indian cities by Harding et al. (2016) documented criticisms that the auto-rickshaw system and its operating drivers face. A balanced aspect is provided between the debate of underlying public perception of the criticisms and their ground reality. Mani et al. (2012) conducted a perception-based study to understand the negative perceptions of developing a sustainable auto-rickshaw system. A detailed review of market characteristics, emissions, safety, and socio-economics, is presented in Mani and Pant (2012). Varghese and Jana (2018) utilized data from auto-rickshaw commuters to investigate Information and Communication Technologies (ICT) use and access by commuters.

Most flexible transportation services like auto-rickshaws are limited to only developing nations. Therefore, a practical perspective on how developed nations can learn from developing nations and integrate flexible transportation services into their societies is provided by Finn (2012). A recent study by Devulapalli and Agrawal (2017) attempted to show the importance and use of open geospatial data in mapping transit systems. Shared auto-rickshaw services are mapped for Hyderabad combined with bus services, thus, portraying opportunities to solve underlying problems. Some studies also attempted to compare different modes with auto-rickshaws. For example, Basu et al. (2017) compared paratransit such as auto-rickshaws with dial-a-cab taxi services for Mumbai and Kolkata using Revealed Preference (RP) data from commuters. The study also suggested that future research fills a knowledge gap in formulating policies supporting auto-rickshaws by performing choice experiments using SP data with different services. Another study by Rastogi and Rao (2003) compared auto-rickshaws with buses and private vehicles using RP and nested SP data. An environmental transit accessibility index is developed to understand commuters' mode share under multiple hypothetical scenarios. Further, Shirgaokar (2019)

Table 2
Literature review of related studies focused on auto-rickshaws in India.

Author	Focus	Region	Method	Recommendation
Das and Mandal (2021)	Commuter perception	Mumbai	Survey, Structural Equation Modeling (SEM)	Improving behavioral intentions of commuters toward sharing auto-rickshaws is important to support service quality.
Priye et al. (2021)	Socio-economic characteristics and operations	Delhi	Survey, Grey-relation analysis	Adoption of sustainable auto-rickshaw models also depends on drivers' perceptions.
Ansari and Sinha (2020)	Socio-economic characteristics and operations	Patna	Survey, Importance-performance analysis	Service quality offered by auto-rickshaws is vital for user perception.
Fleitoukh and Toyama (2020)	Socio-economic characteristics and operations	Delhi	Survey, Regression analysis	Drivers perceive sharing auto-rickshaw services as a low-income source.
Priye and Manoj (2020)	Socio-economic characteristics and operations	Patna	Survey, Multinomial logistic regression	Future studies should compare user perceptions with non-user for better insight.
Sharma et al. (2020)	Socio-economic characteristics and operations	Kolkata	Survey, RIDIT technique	Users give more importance to qualitative attributes than quantitative ones. Future works should assess heterogeneity among users.
Basu (2019)	Market characteristics	Kolkata	SWOT (Strengths, Weaknesses, Opportunities, and Threats) analysis	Auto-rickshaws need to integrate with technologies to improve their service and stay competitive.
Danesh et al. (2019)	Market characteristics	Mumbai	Survey, Logit model	Focusing on attitudinal variables of users is important in auto-rickshaw mode choice.
Kumar and Roy (2019)	Policy direction	Delhi	Literature review	Lack of focus from policymakers is deterring development in the auto-rickshaw system.
Behl et al. (2018)	Market characteristics	India	Survey, Interpretive Structural Modeling (ISM)	Regulatory pitfalls are stopping auto-rickshaw systems from operating efficiently using a fleet-based structure.
Bisht and Ahmed (2018)	Socio-economic characteristics and operations	Silchar	Survey, Utility mapping	Auto-rickshaw is the primary transportation mode, which is informally operated. Authorities should start supporting the modes and cover them under a structured module.
Muralidhar et al. (2018)	Market characteristics	Bengaluru	Survey, Interview, Data pattern technique	Integration and technology awareness increase ease of operation for drivers of auto-rickshaws, which may translate into better service to users.
Basu et al. (2017)	Market characteristics	Mumbai, Kolkata	Survey, Structural Equation Modeling (SEM)	There is a need to include paratransit in future urban transportation system policymaking.
Harding et al. (2016)	Policy direction	India	Literature review, Survey	There is a lack of policy reforms by policymakers on the auto-rickshaw system due to negative perceptions.
Kumar et al. (2016)	Policy direction	Amritsar, Jaipur, Noida, Ahmedabad-Gandhinagar, and Sanand-Viramgam	Literature review, Survey	The negative impact on service performance of informal transportation modes, such as sharing auto-rickshaws, is due to a lack of recognition from policymakers.

compared auto-rickshaws with other modes of transportation based on choice differences among different genders using a psychological framework containing time and safety constraints. Shirgaokar (2019) also suggested that as India has a mushrooming middle class with increasing women participation, women as a gender group proactively make preferences and travel choices. Women have different travel requirements as compared to men. There is a lack of studies that attempt to estimate the preferences of women commuters in auto-rickshaws. Thus, separate studies should be conducted on commuting women (living in societies with inherent gender roles) for policymaking. Table 2 highlights a literature review of studies on auto-rickshaws in India based on the different areas of focus discussed above.

2.3. Research gaps and motivation

There is a need to perform choice experiments involving multiple distinct service types to fill the knowledge gap in auto-rickshaw system policies (Basu et al., 2017). Understanding current users' experiences and expectations of potential users could help develop robust policies to make non-users adopt a mode (Das and Mandal, 2021; Deb and Ahmed, 2018). There is a lack of studies that combines knowledge from users and non-users. Shirgaokar (2019) suggested that India has highly heterogeneous socio-economical characteristics and that understanding the characteristic variations is vital to developing policies. A lack of studies has attempted to model and understand the preferential changes among different socio-economic groups of sharing auto-rickshaw users (Das and Mandal, 2021). It is still unexplored to understand WTP for possible improvements among sharing auto-rickshaw users and their variability within different socio-economic groups.

Therefore, within this study's context of increasing adoption of sharing auto-rickshaws and elevating awareness among operators and policymakers, the present study attempts to overcome the aforementioned research limitations. Some specific aspects included in the current study are.

a. The current study is one of the few studies that attempted to explore sharing auto-rickshaws;
b. Inclusion of choices from both users and non-users makes the results robust;
c. Assessment of WTP and variations among different socio-economic groups support future asset utilization.

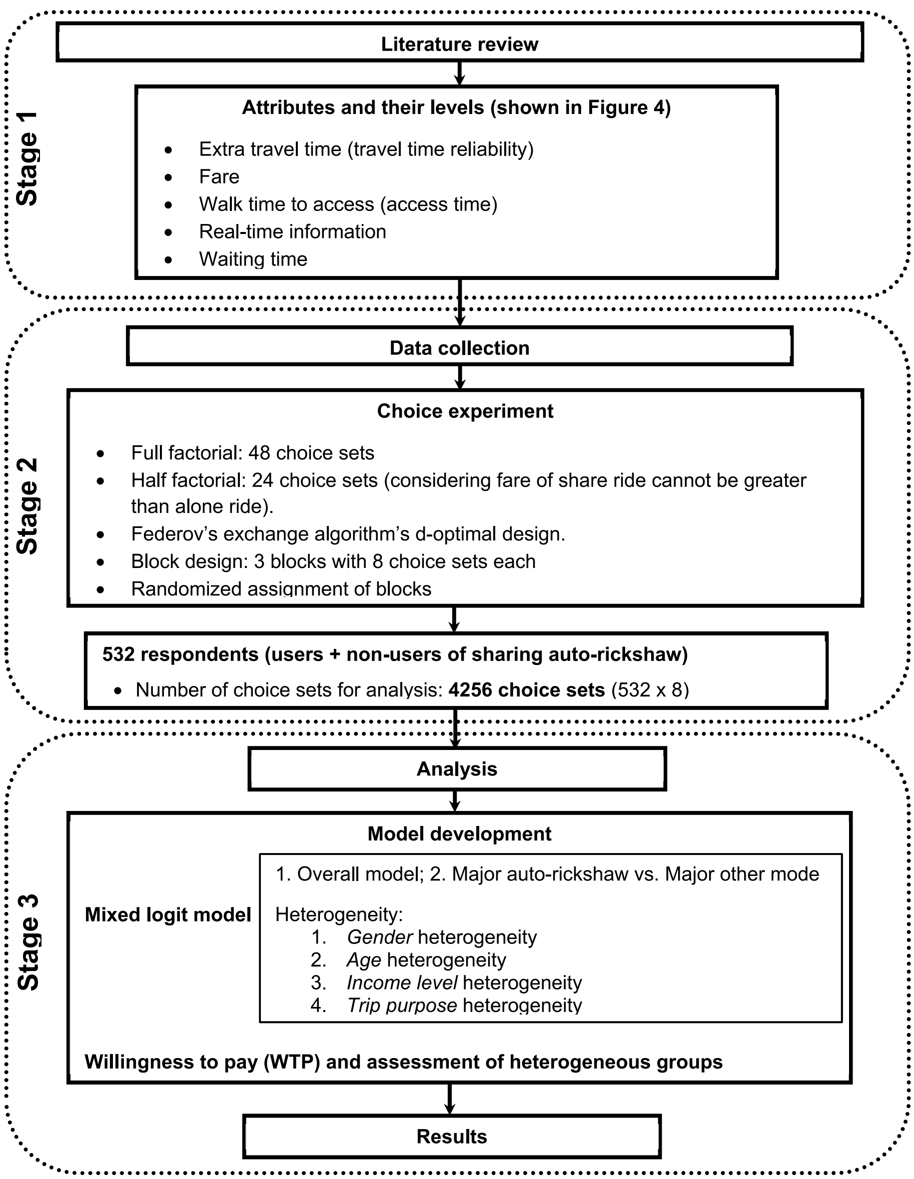


Fig. 2. Methodology diagram.

3. Methodology and data

A detailed methodology flow diagram is presented in Fig. 2, which is majorly divided into three stages. A literature review of studies on auto-rickshaws in India is conducted in the first.

Stage, and attributes are identified that significantly influence mode choice of auto-rickshaws. Data collection is conducted using an optimal number of SP choice sets using a questionnaire in the second stage. ML models are developed using choice sets responses in the third stage and analyzed for interpretation of results. Details on the case study area, design of questionnaire, data collection process, and model structure for data analysis are provided in subsequent sub-sections.

3.1. Case study

MMR is the largest urban agglomeration in India (Bhatia et al., 2022). MMR has a population of 24.4 million, which constitute 92 percent of urban population. The total population is projected to reach 34 million by 2031 (MMRDA, 2008, 2016). According to TERI (2015), Greater Mumbai, Thane, and Navi Mumbai represent MMR (refer to Fig. 3). Thane and Navi-Mumbai fall under the Thane district. Economic and population growth shows upward trends in these two areas (Greater Mumbai and Thane district), leading to a significant increase in vehicular traffic. The two areas share a common boundary, and many commuters travel in-between the areas. Additionally, air pollution is a significant issue in these two areas due to traffic congestion. Air pollution and climate change have a direct relationship. Being in coastal regions, MMR is highly susceptible to threats of climate change. Air pollution and traffic congestions propagate health issues and waste valuable time. Most auto-rickshaws are forced to opt for a cleaner fuel such as Compressed Natural Gas (CNG) in MMR to counter air pollution and its associated ill effects. Therefore, promoting sharing auto-rickshaws can provide additional environmental benefits (TERI, 2015).

Considering the problems are majorly localized in Greater Mumbai and Thane districts, this study considered a combined area of Greater Mumbai, Thane, and Navi-Mumbai as a case study (refer to Fig. 3). The majority of responses were collected from Greater Mumbai (Eastern Suburban.

Western Suburban, and Island city). In the current study, the island

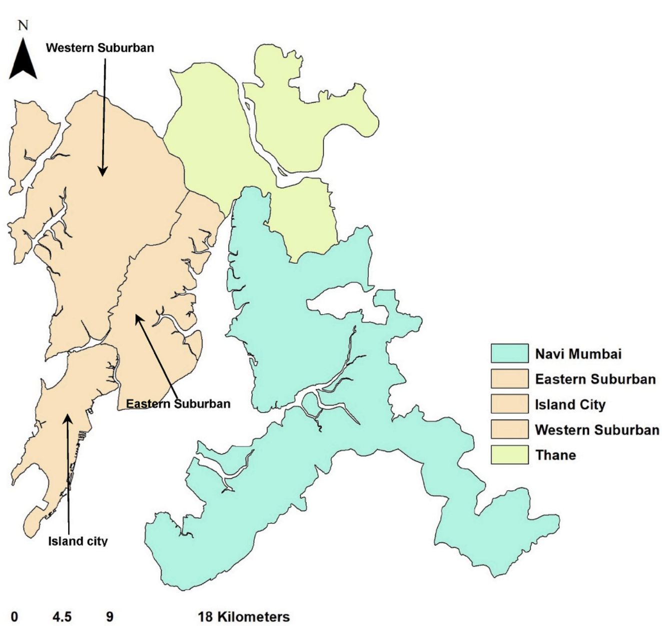


Fig. 3. Case study area (Island city is not selected for data collection).

city of Greater Mumbai has not been considered, as auto-rickshaws are prohibited from operating in the area. MMR's transportation problems are severe and complex due to high population density, lack of land for development, and inadequate roads. There is an urgent need to address its transportation and infrastructural issues through special studies for a sustainable future (MMRDA, 2016; Shafizadeh-Moghadam and Helbich, 2015). Auto-rickshaws account for 11 percent of the total vehicle count and 20 percent of overall trip share among motorized road transportation modes (Mani and Pant, 2012); thus, showing a significant fraction of ridership to auto-rickshaws and the importance of focusing on auto-rickshaws in MMR (Basu et al., 2017; Varghese and Jana, 2018). Similarly, sharing auto-rickshaws caters to 10% of all motorized trips in MMR and runs on over 1000 fixed routes (Meena et al., 2019; Mishra, 2018). Lack of policy support for sharing auto-rickshaws is a primary cause of a rampant increase in illegal sharing auto-rickshaw routes, where 70% of sharing auto-rickshaws are illegal and prone to violating traffic norms and cost structure designated by the Hakim Committee (Das and Mandal, 2021; Mishra, 2018). Therefore, considering a revival of sharing transportation post relaxation of COVID-19 guidelines in MMR, studies need to divert policymakers' attention toward sharing auto-rickshaws and support an increase in adoption among commuters (Das and Mandal, 2021).

3.2. Stated preference survey design

One of the objectives of this study is to understand preferential parameters among auto-rickshaw users towards sharing auto-rickshaws. Discrete choice experiments employ an SP survey to complete the objective (Basu et al., 2017; Sweet, 2021). The choice experiment included five attributes, i.e., '*extra travel time*', '*fare*', '*walking time to access*', '*real-time travel information*', and '*waiting time*'. A sample representation of a question from the SP survey and attributes with their levels is shown in Fig. 4.

Fare levels are decided based on the Hakeem committee's recommendations for Maharashtra (Committee, 2017). Walking time to access service levels are selected based on walking speed ranging from 1.2 to 1.4 m/s, and walking distance to public transportation stops ranging from 300 to 500 m (Advani and Tiwari, 2005; Alshalalfah and Shalaby, 2007; Mohler et al., 2007). The development of choice sets in the SP survey must consider feasible parameters. For example, waiting time and travel time should not be zero. The situations could be proposed but should be realistic (Dell'Olio et al., 2011).

The full factorial of the choice experiment involves 48 choice sets. Rationally, fare for a shared ride cannot be higher than for a single ride. All choice sets from a full factorial design may not be necessary to assess mode choice; therefore, Federov's exchange algorithm for d-optimal design can reduce the number of choice sets. Therefore, this study utilized the 'optFederov' function from the 'Algdesign' package in R to reduce 48 choice sets to 24 (Wheeler and Braun, 2022). Additionally, a higher number of choice sets for a respondent is time-consuming and may cause fatigue. Thus, dividing large choice sets into blocks of smaller choice sets (ranging from 6 to 18 choice sets per block) for each respondent is necessary. In this study, 24 choice sets are divided into three blocks of 8 choice sets, each using the 'optBlock' function. Stated preference data can be combined with RP data from commuters with heterogeneous socio-economic characteristics to estimate preferential variations.

3.3. Data collection and organization

The data collection process involves an online questionnaire. The questionnaire is divided into three parts. The first part contains a letter explaining the purpose of the survey, approximate time required to fill the whole questionnaire, assurance of confidentiality towards their personal information, difference between an alone ride and a shared ride, and researchers' contact information in case of an inquiry. The

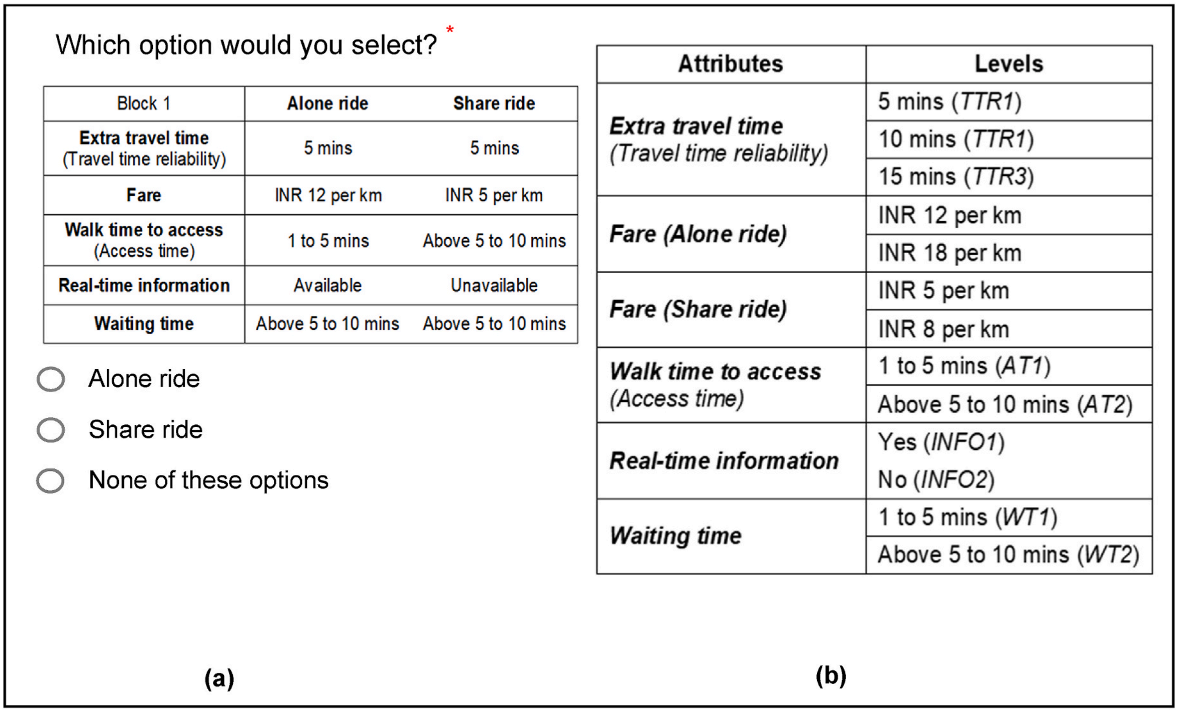


Fig. 4. a) Sample question representation of stated preference survey, b) attributes and their levels. (Note: INR is Indian Rupee (₹), where 1 US$ = 72.21 ₹ on 6th December 2018).

second part collects respondents' RP data for descriptive statistics and understanding heterogeneity in the socio-economic profile. The last part of the questionnaire presents choice experiments to respondents.

Before starting real data collection, a pilot survey was conducted over randomly selected 14 sharing auto-rickshaw users within a University campus. Remarks and suggestions from the pilot survey improved the questionnaire for language, structure, and clarity. The pilot survey outcome showed that people presume rewards for their time in completing the questionnaire, and even after giving assurance of confidentiality, people were wary of giving any of their personal information. Thus, the final questionnaire removed the address row and added name and email-id (or contact number) as identifiers. Thus, formally segregating the respondents as per their actual auto-rickshaw use location is not possible. Descriptions of the attributes (refer to Fig. 4) were not included in the questionnaire because the researchers offered detailed instructions and explanations with examples to each respondent before providing them with the survey questionnaire. The data collection process employed both researcher-administered and self-administered techniques based on the convenience of respondents. Three sets of questionnaires were developed, including three different blocks of choice sets (detail given in section 3.2). To counter selection bias, 'Google script' was used to assign question blocks randomly to respondents (Tanaka et al., 2014).

The minimum number of choice sets requirement is estimated using the following equation provided by Rose and Bliemer (2013) and Orme (2019) for SP studies.

$$N * c > 500 * \left(\frac{l^{max}}{a}\right) \tag{1}$$

Here, N is the sample size, c is the number of choice tasks, l^{max} is the

Table 3
Socio-economic profile of respondents (n = 532).

Characteristics	Observation	Percentage	Characteristics	Observation	Percentage
User Auto-sharing			**Occupation**		
Yes	391	73.50	Formal	436	81.95
No	141	26.50	Student	53	9.96
Gender			Informal, Unemployed, Homemaker, Retired, Other	43	8.09
Female	222	41.73			
Male	310	58.27	**Income/month**		
Auto-rickshaw mode purpose			<INR 20,000	193	36.28
Mandatory	241	45.30	INR 20,000 to < INR35,000	165	31.02
Maintenance	83	15.60	INR 35,000 to < INR 50,000	97	18.23
Discretionary	54	10.15	>INR 50,000	77	14.47
Return to home	91	17.11	**Vehicle own**		
Other	63	11.84	***Two-wheeler***		
Education			Yes	306	57.52
Primary schooling, Middle schooling, High schooling	19	3.57	No	226	42.48
			Car		
			Yes	142	26.69
Graduation	290	54.51	No	390	73.31
Post-graduation	221	41.54	**Major mode**		
Doctorate	2	0.38	Auto-rickshaw	184	34.59
			Other	348	65.41

largest number of levels for any attribute, and a is the number of alternatives. The total responses collected for this study are from 532 commuters, i.e., 4256 (532 × 8) choice sets, significantly higher than the estimated minimum requirement of 750 choice sets. The description of the respondents is given in Table 3.

The majority of data is collected from sharing auto-rickshaw commuters because the current study's requirement focuses on sharing auto-rickshaws. Therefore, the representation of sharing auto-rickshaw users is 73.50 percent. The gender split in the data is 41.73 percent female and 58.27 percent male. Lower sample representation for women is attributed to lower women's participation outside their homes, comparable to 38.70 percent, as Varghese and Jana (2018) reported. Similarly, the mean and median ages are 26.09 and 26 years, respectively, similar to India's population characteristics (OGD, 2019). A higher percentage of mandatory trips using auto-rickshaws, educated respondents, and formal occupations are expected due to the focus of data collection on traveling commuters. Additionally, 57.52 percent reported owning a two-wheeler and 26.69 percent personal car, comparable to numbers reported by Varghese and Jana (2018) for Mumbai. Auto-rickshaw is a major mode of transportation for 34.59 percent, as many commuters use multiple modes to complete a trip.

3.4. Comparison of heterogeneous groups

Varghese and Jana (2018) suggested that Indian society is socio-economically highly heterogeneous. Neglecting heterogeneity may lead to false conclusions about benefits and costs (Ettema and Verschuren, 2008). Therefore, associated heterogeneity develops possible confusion related to the results during choice experiments. Moreover, recent studies have suggested that heterogeneity for different population sub-groups is worth investigating (Bera and Maitra, 2022). The segmentation technique suggested by Koppelman and Bhat (2006) is followed to understand heterogeneity. The market segmentation technique is helpful to counter heterogeneity issues in which groups are developed, which are comparatively homogenous, and they are compared to better understand the problem and effects of heterogeneity. The present study includes a statistical test (chi-square test), referred to as the market segmentation or taste variation test, to determine the statistically different population (trip-makers) segments following previous studies (Athira et al., 2016; Dandapat and Maitra, 2020). Only those segments are reported for which the chi-square value is significant at 99% CI. Hence, the present study attempted to measure preference heterogeneity by comparing different socio-economic and trip characteristics and reported the results for a) *gender* heterogeneity: female with male; b) *age* heterogeneity: younger generation with older generation; c) *income* level heterogeneity: low individual income with high individual income; and d) trip purpose heterogeneity: commuting with non-commuting. The respondents' mean age is 26 (OGD, 2019); therefore, anyone less than or equal to 26 is considered the younger generation, and above is the older generation. According to CVoter (polling agency in India), India has no official definition of dividing the population into income groups. Therefore, CVoter surveyed 1942 randomly selected people and documented respondents' opinions on their income category. The survey results suggest that an individual income of less than INR 23,771 falls under the lower-income group (Rukmini, 2015). Therefore, in the present study, the respondents' group nearest to INR 23,771, i.e., less than INR 20,000, is considered the low individual income group. All mandatory trips are part of commuting, whereas other flexible trips are part of non-commuting. Detailed results related to each type of heterogeneity are discussed in the subsequent paragraphs.

4. Model structure

This section discusses the theoretical framework and assumptions of the ML models. The ML model structure has evolved from the MNL framework. MNL is based on random utility theory, which states that a decision-maker has complete information and rationality while choosing the alternative. At the same time, a person chooses the alternative having the highest utility, where the utility of an alternative i to a person n has the form:

$$u_n(i) = u(x_{in}, s_n) \tag{2}$$

Where, x_{in} is the vector of the attribute of the alternative i for individual n, and s_n is the vector of characteristics of the person n.

The utility has a linear-in-parameter separable form:

$$u(x_{in}, s_n) = V(x_{in}, s_n) * \beta + \epsilon_{in} \tag{3}$$

Where, V is the observed component of utility, β is the parameter vector that would be estimated using the available choice data. The unobserved variable ϵ_{in} represents the vector of random error terms. In the MNL model, β terms are assumed to be equal for all respondents, which is highly unlikely in an actual situation. Additionally, in MNL, a change in one alternative's attributes will change the choice probability of other alternatives in proportion (Train, 2009). On the other hand, ML models are extensively used to avoid such shortcomings, which allows for random taste variation, unrestricted substitution patterns, and correlation in unobserved factors over time. The present study successfully employs the ML models to detect the *panel effects* and *inter-individual preference heterogeneity*. The ML probability for the choice of consumer n, i.e., j_n^* can be expressed as (Hess and Train, 2011):

$$P\_n(j_n^* | \Omega) = \int_\beta P_n(j_n^* | \beta)\, g(\beta | \Omega)\, d\beta \tag{4}$$

Where, β_n is the vector of true but unobserved taste coefficients with density distribution $g(\beta| \Omega)$.

The log-likelihood (LL) function is depicted by:

$$LL\ (\Omega) = \sum_{n=1}^{N} \int_\beta P_n(j_n^* | \beta)\, g(\beta | \Omega)\, d\beta \tag{5}$$

in this case, the integral could not be estimated analytically as choice probability (P) does not have a closed-form solution. Instead, a simulation method must be used to capture the inter-respondent heterogeneity and panel effects. The quasi-random maximum simulated likelihood estimator using Halton draws has been utilized in the present study (Bhat, 2001; Majumdar and Mitra, 2019). The significant advantage of using Halton draws lies in reducing the number of draws, run time, and simulation error. Bhat (2001) indicated that even 125 Halton draws provide comparable accuracy to 2000 pseudo-random draws. Finally, we employ 1000 Halton draws for simulation to approximate log-likelihood (R number of draws), resulting in simulated log-likelihood (SLL):

$$SLL\ (\Omega) = \sum_{n=1}^{N} \ln\left(\frac{1}{R} \sum_{r=1}^{R} P_n(j_n^* | \beta_{r,n})\right) \tag{6}$$

At the same time, Hess et al. (2006, 2017) observed that log-normal distribution is useful when the coefficient estimates have the same sign for all decision-makers, and thus we adopted a negative log-uniform distribution. Additionally, the ML models are estimated in the WTP space as understanding choice makers' WTP can help promote alternatives and policy development (Kraeusel and Möst, 2012). Besides, WTP is an accurate proxy for consumers' buying intentions, especially when alternatives have both price and non-price attributes (Aizaki et al., 2014).

5. Results and discussion

Before initiating the model development and analysis process, necessary checks for incompleteness of data, abbreviations, and coding of variables are completed. The present study used Apollo software

(Hess and Palma, 2019) to estimate the ML model's coefficients.

Travel time reliability (TTR), Walk time to access (ACT), and Waiting time (WT) are estimated directly in WTP space for being a travel time component, whereas the coefficient for real-time information (INFO) has been estimated outside WTP space. The utility equations for the alone auto-rickshaw ride and shared auto-rickshaw ride have been provided below:

$$V_{alone\_ride} = asc\_1 + b\_fare * (v\_TTR * TTR\_alone + v\_WT * WT\_alone + v\_ACT * ACT\_alone + fare\_alone) + b\_INFO * INFO\_alone \quad (7)$$

$$V_{shared\_ride} = asc\_2 + b\_fare * (v\_TTR * TTR\_shared + v\_WT * WT\_shared + v\_ACT * ACT\_shared + fare\_shared) + b\_INFO * INFO\_shared \quad (8)$$

where, 'asc' is alternative specific constant, 'b' is coefficient of respective variables, and 'v' is the WTP value of respective variables. It is worth mentioning that 'asc_2' (i.e., alternative specific constant for shared auto-rickshaw ride) has been kept fixed at 0 (base value). No user characteristics are included in the utility equations because the improvement in goodness-of-fit is not significant. Therefore, by following the approach by Li et al. (2017), it is determined that an insignificant increase in goodness-of-fit is not worth raising the model's complexity. Consequently, the present study estimated WTP values for segmented homogenous groups instead.

Table 4 provides details of the estimated significant coefficients and the associated average WTP values for the overall model for users and non-users of sharing auto-rickshaw services. Table 4 includes results from both ML and MNL models for comparison based on the suggestion of Bera and Maitra (2022) and Ma et al. (2019).

The likelihood test ratio is used to compare the performances of MNL and ML models. The test statistic used is provided by -2 (L_{MNL} - L_{ML}), which follows chi-square (χ^2) distribution (asymptotically) with a degree of freedom (dof) of 5 (Ben-Akiva and Lerman, 1985). Log-likelihood of the MNL model is represented by L_{MNL}, whereas L_{ML} depicts log-likelihood for the ML model. Now, for a 95% confidence interval, i.e., a level of significance of 0.05, we have $\chi^2_{0.95,5} = 11.07$. Based on the estimation results as shown in Table 4 and it could be observed that:

$$-2\ (L_{MNL} - L_{ML}) = -2\ (-2654.77 + 1883.57) = 1542.40 > 11.07$$

The results infer that ML model fits much better than the MNL model, i.e., the preference heterogeneity is of utmost importance and should be included in the estimation process. Therefore, further analysis results are presented using the ML model. The adjusted rho-squared value for the overall model and all five comparison models are within the range of 0.3–0.4, thus suggesting a good model fit (Ortúzar and Willumsen, 2011).

For estimation purposes, the alternative specific constant for the shared auto-rickshaw ride (asc_2) has been treated as the base and fixed at 0. It is worth mentioning that all the coefficients using ML model turn out to be statistically significant at a 99% confidence interval (CI) for the overall model in Table 4 and the comparison of regular users with non-regular users in Table 5 with signs and estimated values as expected. Although the interpretation of the estimates is not straightforward, as explained in Section 4. Hence, as mentioned before, WTP associated with each attribute is estimated and interpreted as the user's perceived benefit for each unit change in the attribute. All the variables have been treated as random with log-normal distribution, including the cost parameter, i.e., 'fare', which explains the underlying variation better. Although the real-time information parameter, i.e., INFO, has been estimated in the model, we avoided its WTP calculation as a fixed unit of INFO cannot be readily perceived.

The overall model results in Table 4 indicate that WTP is highest for 'TTR' among all travel time-related attributes. Respondents are willing to pay INR 0.28/minute more per trip to improve travel time reliability, i.e., on-time arrival to destination. The WTPs for ACT (INR 0.26/minute) and WT (INR 0.19/minute) closely follow TTR. The information parameter 'INFO' also turns out to be significant with a positive average value (INR 21.56), suggesting that the availability of real-time information seems an essential factor among auto-rickshaw commuters.

In MMR, generally, commuters complete a single trip to their destination using multiple modes. The mode used to complete the major portion of a trip is considered a major mode of travel for that particular respondent (Varghese and Jana, 2018). In this study, data is collected from both commuters for whom 'major mode is auto-rickshaw (MA)' and for whom 'major mode is other modes (MO)'. It is expected that there might be significant differences in WTP values for MA and MO. That is why WTP estimates have also been separately calculated for these two subgroups in Table 5. The comparison reveals that WTP values are sensitive to use frequency, majorly for ACT and WT. This outcome is intuitive. In the typical Indian context, MA commuters are mostly captive with lower average monthly family income than MO commuters; MO commuters are willing to pay more than the MA commuters because of the comparatively higher-income level. Interestingly, both MA and

Table 4
Estimation results for the overall model.

	ML model				MNL Model			
	Estimate	Robust t-stat	Sig.	Average WTP	Estimate	Robust t-stat	Sig.	Average WTP
***ASC* (Alternative specific coefficient)**								
Alone ride	1.96	10.56	***		−0.519	−5.09	***	
***Random* (in WTP space)**								
Travel time reliability (mean)	−1.94	−9.45	***	**0.28**	−0.045	−6.02	***	**1.04**
Travel time reliability (std. dev.)	−1.13	−9.91	***					
Waiting time (mean)	−4.64	−10.29	***	**0.19**	−0.016	−2.53	**	**0.37**
Waiting time (std. dev.)	2.49	11.89	***					
Access time (mean)	−2.67	−5.00	***	**0.26**	−0.013	−1.81	*	**0.31**
Access time (std. dev.)	−1.60	−5.47	***					
Random				Average Value				Average Value
Real-time information (mean)	−4.46	−15.93	***	21.56	0.177	5.68	***	
Real-time information (std. dev.)	3.90	20.30	***					
Travel cost (mean)	−4.05	−18.59	***	−3.06	−0.043	−5.10	***	
Travel cost (std. dev.)	7.11	15.09	***					
Model fit								
N	4256.00				4256.00			
log-likelihood	−1883.57				−2654.77			
ρ^2_{adj}	0.36				0.01			

*** 99% *significance* level, ** 95% *significance* level, * 90% *significance* level.

Table 5
Estimation results for comparison based on major mode of travel.

	Major auto-rickshaw				Major other			
	Estimate	Robust t-stat	Sig.	Average WTP	Estimate	Robust t-stat	Sig.	Average WTP
***ASC* (Alternative specific coefficient)**								
Alone ride	2.50	6.40	***		1.77	8.17	***	
***Random* (in WTP space)**								
Travel time reliability (mean)	−1.46	−245.07	***	**0.32**	−1.87	−13.83	***	**0.31**
Travel time reliability (std. dev.)	−0.77	−172.97	***		−1.20	−19.11	***	
Waiting time (mean)	−3.59	−30.41	***	**0.15**	−4.01	−3.64	***	**0.17**
Waiting time (std. dev.)	1.81	34.42	***		2.12	4.47	***	
Access time (mean)	−2.45	−76.33	***	**0.38**	−3.11	−10.56	***	**0.27**
Access time (std. dev.)	−1.69	−102.43	***		−1.88	−12.74	***	
Random				Average Value				Average Value
Real-time information (mean)	−4.38	−11.29	***	8.50	−3.73	−5.04	***	3.81
Real-time information (std. dev.)	3.58	15.98	***		3.15	8.83	***	
Travel cost (mean)	−3.92	−14.37	***	−29.42	−4.26	−18.51	***	−2.28
Travel cost (std. dev.)	9.62	11.85	***		7.05	14.30	***	
Model fit								
N	1472.00				2784.00			
log-likelihood	−567.22				−1303.15			
ρ^2_{adj}	0.43				0.32			

*** 99% *significance* level, ** 95% *significance* level, * 90% *significance* level.

MO commuters perceive TTR as equally important, whereas opposite trends can be observed for ACT and WT. MO commuters are willing to pay more (INR 0.17/minute) to reduce WT relative to MA commuters (INR 0.15/minute), whereas a reverse trend can be observed for the ACT as MA commuters are willing to pay INR 0.38 for each minute's reduction in access time to auto-rickshaw stop as compared to INR 0.27 for their non-regular counterparts. This is intuitive because non-regular users, because of their infrequent trip-making nature, can easily perceive the importance of in/out of vehicle travel time (IVTT/OVTT) rather than recognizing the potential benefit of reducing access time. This reasoning is reinforced when the WTP for INFO for regular users is higher than for non-regular users as they use the said alternative occasionally. To understand heterogeneity, the upcoming sub-section highlights the comparative ML models of different segmented homogenous groups.

5.1. Heterogeneous group comparisons

Table 6 indicates that all the parameters are significant for both female and male commuters. It reveals that the WTP value for both TTR (INR 0.20/minute) and ACT (INR 0.24/minute) for women is lower as compared to men (INR 0.35/minute and INR 0.35/minute), with a comparable WTP value for WT (INR 0.12/minute). This might be attributed to the financial dependence of a significant share of female sub-population on their spouses in a typical Indian context, leading to lower affordability. Interestingly, INFO's importance for women (20.33) has been highlighted, which indicates a real-time information system could minimize security issues by increasing transparency and the possibility of sharing live travel information with family and friends. This is in line with earlier findings, which suggest that crime against women is a major issue in transportation (Shirgaokar, 2019), and secured public transportation is a priority for females (Javid et al., 2015). The security

Table 6
Estimation results for gender heterogeneity.

	Female				Male			
	Estimate	Robust t-stat	Sig.	Average WTP	Estimate	Robust t-stat	Sig.	Average WTP
***ASC* (Alternative specific coefficient)**								
Alone ride	2.14	7.22	***		1.83	7.73	***	
***Random* (in WTP space)**								
Travel time reliability (mean)	−2.20	−7.56	***	**0.20**	−1.75	−12.19	***	**0.35**
Travel time reliability (std. dev.)	−1.07	−8.11	***		−1.14	−14.22	***	
Waiting time (mean)	−3.67	−2.02	***	**0.12**	−3.65	−7.61	***	**0.11**
Waiting time (std. dev.)	1.74	2.37	***		1.73	8.19	***	
Access time (mean)	−3.74	−7.87	***	**0.24**	−2.29	−1.98	***	**0.35**
Access time (std. dev.)	−2.23	−9.21	***		−1.59	−2.64	***	
Random				Average Value				Average Value
Real-time information (mean)	−3.84	−8.51	***	20.33	−4.77	−1.92	***	2.96
Real-time information (std. dev.)	3.82	11.84	***		3.55	2.13	***	
Travel cost (mean)	−3.97	−13.96	***	−5.59	−4.22	−4.05	***	−2.96
Travel cost (std. dev.)	7.78	10.95	***		7.31	2.49	***	
Model fit								
N	1776.00				2480.00			
log-likelihood	−729.44				−1147.72			
ρ^2_{adj}	0.40				0.33			

*** 99% *significance* level, ** 95% *significance* level, * 90% *significance* level.

Table 7
Estimation results for age heterogeneity.

	Younger generation (≤26 Year)				Older generation (>26 Year)			
	Estimate	Robust t-stat	Sig.	Average WTP	Estimate	Robust t-stat	Sig.	Average WTP
ASC **(Alternative specific coefficient)**								
Alone ride	1.69	5.54	***		2.16	8.71	***	
Random **(in WTP space)**								
Travel time reliability (mean)	−2.41	−12.18	***	**0.41**	−1.84	−7.81	***	**0.28**
Travel time reliability (std. dev.)	−1.73	−16.65	***		−1.07	−8.15	***	
Waiting time (mean)	−5.50	−10.20	***	**0.05**	−3.64	−16.79	***	**0.29**
Waiting time (std. dev.)	2.20	11.07	***		2.27	21.29	***	
Access time (mean)	−3.16	−7.60	***	**0.40**	−3.83	−10.85	***	**0.27**
Access time (std. dev.)	−2.11	−7.21	***		−2.30	−11.60	***	
Random				Average Value				Average Value
Real-time information (mean)	−3.34	−1.91	***	2.56	−4.94	−10.42	***	31.76
Real-time information (std. dev.)	3.19	2.95	***		4.34	20.27	***	
Travel cost (mean)	−4.08	−12.10	***	−5.79	−4.22	−18.37	***	−3.11
Travel cost (std. dev.)	7.88	6.89	***		7.36	14.48	***	
Model fit								
N	1680.00				2576.00			
log-likelihood	−700.04				−1173.18			
ρ^2_{adj}	0.39				0.34			

*** 99% *significance* level, ** 95% *significance* level, * 90% *significance* level.

issues involve unruly behavior from co-passengers and drivers (Basu et al., 2017) and a lack of route information on shared auto-rickshaws.

Now, the comparison between age groups in Table 7 shows higher WTP values for both TTR (INR 0.41/minute) and ACT (INR 0.40/minute) for the younger generation, whereas a reverse trend can be observed for WT (INR 0.05/minute (which is very low)). The corresponding WTP values for TTR and ACT are 33% and 35% lower in the older generation. This finding holds great importance as it indicates how emerging ICT-based services change youths' travel perceptions where door-to-door deliveries (no access loss) and reliable travel periods are usual norms.

Moreover, WTP values in Table 8 indicate that for low-income individuals, ACT attribute (INR 0.33/minute) is more important than TTR (INR 0.30/minute), whereas opposite trend can be found for individuals with higher income - with corresponding WTPs for ACT and TTR being INR 0.30/minute and INR 0.31/minute, respectively. It must be noted that for WT, very similar WTP can be observed for both income groups, i.e., about INR 0.10/minute. Interestingly, for real-time travel information (INFO), the low-income group is willing to pay 76% more than their high-income counterparts. The underlying reason could be that a significant portion of high-income individuals is infrequent auto-rickshaw users and thus put more importance on travel time than INFO, which is more beneficial for regular users.

Another interesting observation from Table 9 is that respondents are willing to pay more for increasing both TTR and WT in the case of non-commute trips, whereas WTP for ACT is higher for commute trips. The average estimate for INFO also follows a similar direction with a greater value for non-commute trips. The underlying reason for commuters willing to pay less could be that they are more familiar with the service, allowing them to be confident of better recognizing any delays related to scheduled and on-board times (Bellizzi et al., 2020; Eldeeb and Mohamed, 2022; Gao et al., 2018).

Table 8
Estimation results for income level heterogeneity.

	Low individual income (< INR 20K)				High individual income (≥20K)			
	Estimate	Robust t-stat	Sig.	Average WTP	Estimate	Robust t-stat	Sig.	Average WTP
ASC **(Alternative specific coefficient)**								
Alone ride	2.09	5.82	***		1.88	8.52	***	
Random **(in WTP space)**								
Travel time reliability (mean)	−2.41	−29.75	***	**0.30**	−1.69	−16.67	***	**0.31**
Travel time reliability (std. dev.)	−1.54	−31.54	***		−1.04	−21.24	***	
Waiting time (mean)	−3.80	−10.46	***	**0.09**	−3.52	−5.73	***	**0.10**
Waiting time (std. dev.)	1.63	11.30	***		1.56	6.74	***	
Access time (mean)	−4.10	−23.28	***	**0.33**	−2.71	−5.48	***	**0.30**
Access time (std. dev.)	−2.48	−24.54	***		−1.77	−7.22	***	
Random				Average Value				Average Value
Real-time information (mean)	−4.02	−8.63	***	8.76	−3.60	−5.14	***	4.96
Real-time information (std. dev.)	3.77	14.83	***		3.27	10.67	***	
Travel cost (mean)	−4.31	−15.04	***	−10.98	−4.08	−16.76	***	−1.88
Travel cost (std. dev.)	8.83	17.66	***		6.58	13.32	***	
Model fit								
N	1544.00				2712.00			
log-likelihood	−588.90				−1285.84			
ρ^2_{adj}	0.44				0.31			

*** 99% *significance* level, ** 95% *significance* level, * 90% *significance* level.

Table 9
Estimation results for trip purpose heterogeneity.

	Trip purpose: Non-Commute				Trip purpose: Commute			
	Estimate	Robust t-stat	Sig.	Average WTP	Estimate	Robust t-stat	Sig.	Average WTP
***ASC* (Alternative specific coefficient)**								
alone ride	2.22	7.48	***		1.40	4.89	***	
***Random* (in WTP space)**								
Travel time reliability (mean)	−1.68	−30.45	***	**0.45**	−2.32	−5.07	***	**0.17**
Travel time reliability (std. dev.)	−1.38	−37.34	***		−1.02	−5.20	***	
Waiting time (mean)	−3.47	−4.32	***	**0.12**	−3.82	−4.17	***	**0.08**
Waiting time (std. dev.)	1.63	3.69	***		1.53	4.98	***	
Access time (mean)	−4.23	−19.76	***	**0.26**	−5.56	−3.34	***	**0.33**
Access time (std. dev.)	−2.42	−21.77	***		−2.94	−3.85	***	
Random				Average Value				Average Value
Real-time information (mean)	−6.17	−8.58	***	28.42	−2.36	−4.01	***	1.30
Real-time information (std. dev.)	4.79	17.49	***		2.24	7.29	***	
Travel cost (mean)	−4.89	−13.63	***	−6.35	−3.58	−15.40	***	−1.68
Travel cost (std. dev.)	8.87	13.43	***		5.87	10.19	***	
Model fit								
N	1600.00				1928.00			
log-likelihood	−673.92				−862.51			
ρ^2_{adj}	0.38				0.35			

*** 99% *significance* level, ** 95% *significance* level, * 90% *significance* level.

5.2. Model validation

As part of the validation exercise, two approaches are followed in the present study. The first approach is concerned with applying the model to the respective estimation sample and calculating the average choice probabilities assigned by the model to the actual chosen alternative, i.e., market share of the alternatives. The following Table 10 confirms that the differences between the prediction share and the observed share are not statistically significant at the level of significance of 0.05 (95% CI). Therefore, we could safely claim that the model has reasonable accuracy.

The second validation approach is to check the ability of the final calibrated model (with a 90% sample) to correctly predict the market shares and choices in data that were not used in the actual model estimation process (with the rest 10% holdout sample). However, doing this with only one validation sample may lead to biased results because a particular validation sample does not need to represent the population. Therefore, the analysis randomly draws 10 pairs of estimation and validation samples from the complete dataset and applies the procedure to each pair, as Bhaduri et al. (2020) suggested. In order to evaluate the efficacy of the validation procedure, a confusion matrix or misclassification matrix was produced for each of the 10 attempts. The results show that prediction accuracy, i.e., aggregate match rate ranges from 70% to 75% for all the 10 runs (refer to Table 11), though the model slightly overestimates the market share of the alone ride and underestimates shared ride. Therefore, combined results from both approaches highlight that the models from the present study have acceptable validity.

Table 10
Model validation with the market share approach.

	Alone ride	Sharing ride	All
Times chosen (data)	1392	2864	4256
Times chosen (prediction)	1435.65	2820.35	4256
Diff (prediction-data)	43.65	−43.65	0
t-ratio	1.42	−1.42	NA
p-val	0.155	0.155	NA

Here, NA means not available.

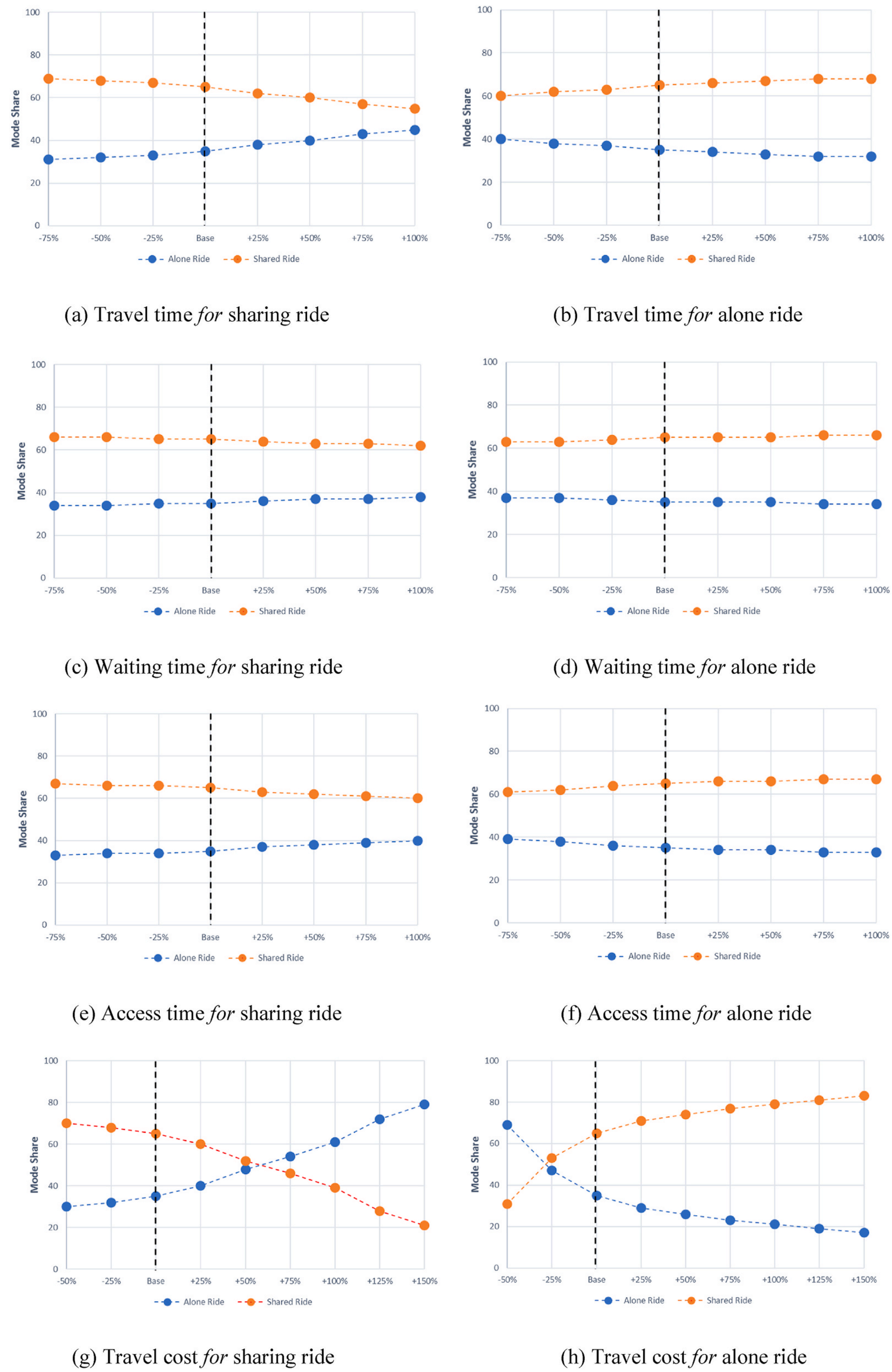
Table 11
Model validation with the simulation approach.

Validation Run	Model Accuracy	Validation Run	Model Accuracy
1	71%	6	73%
2	72%	7	75%
3	70%	8	74%
4	75%	9	75%
5	72%	10	74%

5.3. Sensitivity analysis

The sensitivity analysis (refer to Fig. 5) has been performed for all four key variables- (1) travel time reliability, (2) waiting time, (3) access time, and (4) travel cost. Fig. 5 explains how changes in each of the variables for alone and sharing ride impacts the choice probabilities. The changes (in %) have been calculated based on the range of −75% to +100% in steps of 25%. The analysis limited the lower bound to −50% for travel costs, while the upper bound was extended to +150% to make the estimate more realistic.

Notably, Fig. 5 (a)-(b) demonstrates that reducing travel time (by 25%) for sharing rides could increase its choice probability by 2% points, whereas it rises by 1% points for 50% and 75% reductions. On the other hand, similar trends are shown in the case of alone rides with a 75% reduction in travel time, resulting in a slightly higher increase (5% points) in its mode share. It is worth mentioning that waiting time has the least sensitivity on mode choice probability while access time has relatively more impact (Fig. 5 (c)-(d)). It has been observed that reducing access time for alone rides has a greater impact (1%–2% higher rise in respective share) on mode choice probability than sharing rides (Fig. 5 (e)-(f)). Most importantly, cost reduction for both alone and sharing rides has the most profound impact on mode share, as depicted in Fig. 5 (g)–(h). The choice probability for an alone ride drops by 6% pts to 18% pts for a 25%–150% increase in fare, whereas similar travel cost changes result in a 5% pts to 44% pts drop in the likelihood of choosing sharing mode.



(a) Travel time *for* sharing ride

(b) Travel time *for* alone ride

(c) Waiting time *for* sharing ride

(d) Waiting time *for* alone ride

(e) Access time *for* sharing ride

(f) Access time *for* alone ride

(g) Travel cost *for* sharing ride

(h) Travel cost *for* alone ride

Fig. 5. Sensitivity analysis for (a)–(b) Travel time, (c)–(d) Waiting time, (e)–(f) Access time, and (g)–(h) Travel cost on choice probability of sharing and alone ride.

5.4. Policy implications of the results

Due to the informal operational structure of auto-rickshaws, there are complications involved in promoting sharing auto-rickshaws as a sustainable transportation mode choice (Wright et al., 2014). The current study highlighted the essential attributes in choosing sharing auto-rickshaws corresponding to different socio-economic groups. This subsection points to the demonstrable effects offered by the findings of this study, which can justify a related set of actions.

1. **Recognizing importance:** Section 1 of this study highlights the lack of focus on the auto-rickshaw mode by policymakers and

government due to a lack of knowledge and studies. Even if auto-rickshaws remain informally operational, the study is one of the small steps that should encourage policymakers and government to change their view toward sharing auto-rickshaws by considering it an essential part of the current transportation system and understanding the vital role played by the mode in intra-city connectivity.

2. **Facilitating land use planning**: In India, government and policymakers formulate land-use policies and human housing developments. Therefore, exploiting the full functional potential of development in urban areas' outskirts requires strong transportation linkage. Auto-rickshaw operation requires an insignificant fixed infrastructure. Facilitating auto-rickshaw usage should be helpful until mass transportation infrastructures like bus and railway systems become fully functional. Additionally, the outskirts of cities are majorly underdeveloped and vast, with low population density. Developing buses and railways with significant reach in the areas would not be a viable choice. Therefore, the auto-rickshaw mode could be a better and more flexible mode to promote.
3. **Asset utilization and market understanding**: The study highlights prioritizing attributes like saving extra travel time and providing real-time travel information facilities. Therefore, considering limited resources available, policymakers could accelerate the adoption of sharing auto-rickshaws by providing an initial investment focus on the attributes.
4. **Investment estimation:** WTP values in the analysis could help policymakers calculate an average estimate of investment that should be done and over what time the entire investment may breakeven. The monetary estimations will be robust as the study attempted to estimate WTP for various important socio-economic characteristics.
5. Sensitivity analysis indicates that sharing auto-rickshaw riders are more considerate of waiting time than those who take alone rides. This result implies that, even if the number of auto-rickshaws increased and reduced waiting times, commuters would still opt for private vehicles or solo rides (Maitra et al., 2015). Thus, investing in more auto-rickshaws providing shared services may not be necessary to raise the modal share of shared trips. Similarly, sensitivity analysis also reveals that improving access time benefits single riders more than those riding together. Consequently, investments in increasing the number of auto-rickshaw stands will also not lead to an increase in shared trips. Cost is seen as the most important factor based on sensitivity analysis regarding sharing versus solo rides. It is worth noting that a small change in fare could keep existing users and even cause some commuters to switch from alone rides to shared ones; however, larger percentage of changes start leading people away from group travel. The results emphasize how cost advantage favors traveling together; therefore, push-and-pull policies should be implemented to penalize autorickshaws taking lone passengers and subsidizing costs/taxes for those offering shared services to boost their modal share.

5.5. Limitations and futures scopes

The subsection lists some minor limitations of the current study and the future scope of research.

1. The results should not be generalized as the attribute selection did not consider cultural aspects of an area. Cultural aspects are naturally sensitive and profoundly affect people's behavior and preferences (Das et al., 2021b). Thus, incorporating cultural aspects in future research could improve adoption and delivery of sharing auto-rickshaw services.
2. Respondent profile in the current study is limited to people with the possibility of taking trips, not necessarily using auto-rickshaws as their major mode. The profile may not be a complete representation of real trip characteristics. Future studies should focus on gathering group-specific (for example, commuters with major mode as auto-rickshaw) data or include other respondents' profiles (for example, housemaker and retired).
3. Table 3 highlights that 96% of the respondents have a graduate or above education level, which does not represent accurate MMR representation for commuters. Although it is expected because, as per experience during the survey process, commuters with lower education levels are not familiar with the survey process and are reluctant to provide their view or information. Therefore, future studies can try to provide gifts or direct monetary benefits to commuters for greater participation.
4. Considering the present study's methodological framework, further research could focus on other modes of transportation as preferences vary among commuters. Sharing vehicles is marketed as a sustainable mode of transport; therefore, future studies can explore sharing auto-rickshaws' suitability from underlying three major pillars of sustainability, i.e., environmental, economic, and social (Kalbar and Das, 2020).
5. The study adopted the segmentation approach to separate the endogeneity effect from biased WTP estimates. Relying solely on segmentation may not be enough to address this issue entirely. Therefore, it could be considered a limitation of this study and must be further investigated in future studies.

6. Conclusions

Preferences of auto-rickshaw users and non-users are assessed and modeled using the ML on stated preference choice experiment data for sharing auto-rickshaw. Some major observations from the present study are as follows.

i. In general, 'travel time reliability' is perceived to have the highest WTP value for travelers, closely followed by 'access time'.
ii. The information parameter is also perceived to have positive utility for travelers sharing auto-rickshaw rides.
iii. Commuters whose primary travel mode is auto-rickshaw are willing to pay 40% more for 'access time' than their non-major counterparts.
iv. For females, the significant attribute is on board real-time travel information, and they are willing to pay more relative to men to access real-time travel information.
v. Young people are willing to pay 33% and 35% more for 'travel time reliability' and 'access time', respectively.
vi. Low-income individuals are willing to pay 10% more for 'access time' than their high-income counterparts, highlighting the importance of last-mile connectivity for economically weaker sections. Similar analogies can also be observed for 'real-time information'.
vii. Non-commuters are willing to pay significantly higher amounts to improve the 'travel time reliability' attribute rather than 'access time'.

The results highlight the importance of assessing heterogeneity among commuters. Identifying differences among competing groups based on gender, age, income, and travel purpose are essential for asset utilization and market understanding in a resource-constraint developing nation such as India. The most critical perceived attribute is travel time reliability, consistently among the highest WTP within different groups. The importance of real-time information among female commuters and sharing auto-rickshaw users who share their rides with unknown people is highlighted in the results. It is recommended that in an era of mobile and the internet, providing real-time information is not impossible, but it requires special focus from service providers, which they lack because of the low monetary involvement in auto-rickshaw rides. Similarly, the importance of decreasing access time for commuters for whom auto-rickshaw is a major mode and low-income groups for whom low costing auto-rickshaw rides provide greater ease are highlighted in the study's results. Government involvement and extra push-through policy development will help in such situations. Section 1 'Introduction' and Section 2 'Literature review and research gaps' highlighted a lack of focus and formal policy development on sharing auto-rickshaws due to the absence of knowledge and studies. The present study is one of the first attempts to provide a clear path toward effective and integrated policymaking for sharing auto-rickshaw adoption. Thus, identifying commuters' preferences helps in adopting sharing auto-rickshaws.

Contribution statement

Deepjyoti Das: Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Project administration, Resources, Software, Supervision, Interpretation, Validation, Vizualization, Writing - original draft. **Eeshan Bhaduri**: Formal analysis, Investigation, Methodology, Resources, Software, Interpretation, Validation, Vizualization, Writing - original draft. **Nagendra R. Velaga**: Resources, Supervision, Interpretation, Writing - review & editing.

Data statement

Data will be made available on request.

Declaration of competing interest

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

Data availability

Data will be made available on request.

Acknowledgments

The authors have not received any specific funding to complete this part of the study. Deepjyoti Das would like to thank Ms. Pinky Mandal from HERE Technologies (Navi Mumbai) and Prof. Varun Varghese from Hiroshima University (Japan) for help in data collection and elaborate discussions, respectively. Deepjyoti Das also acknowledges the scholarship from the Ministry of Human Resource Development (MHRD), India, and the Centre of Excellence in Urban Science and Engineering (CUSE) and Chalmers University of Technology for providing all necessary support to complete this part of the study.

References

Abu Mallouh, M., Surgenor, B., Denman, B., Peppley, B., 2011. Analysis and validation of a Powertrain System Analysis Toolkit model of a fuel cell hybrid rickshaw. Int. J. Energy Res. 35 (15), 1389–1398. https://doi.org/10.1002/er.

Advani, M., Tiwari, G., 2005. Evaluation of public transport systems: case study of Delhi metro. In: START-2005 Conference Held at IIT Kharagpur, India, vol. 2003, pp. 1–8. https://pdfs.semanticscholar.org/edf8/5468b8be20d903251ee9b22badd9da2947b7.pdf?_ga=2.256859016.2056643387.1546592780-1618322259.1528452977.

Aizaki, H., Nakatani, T., Sato, K., 2014. *Stated Preference Methods Using R* (Issue C). CRC press (Taylor & Francis Group. https://doi.org/10.1201/b17292.

Alshalalfah, B.W., Shalaby, A.S., 2007. Case study: relationship of Walk access distance to transit with service, travel, and personal characteristics. J. Urban Plann. Dev. 133 (2), 114–118. https://doi.org/10.1061/(asce)0733-9488(2007)133:2(114).

Ansari, M.W., Sinha, S., 2020. Comparative assessment of service quality of ipt modes in Urban India. Civil Engineering and Architecture 8 (6), 1436–1450. https://doi.org/10.13189/cea.2020.080626.

Athira, I.C., Muneera, C.P., Krishnamurthy, K., Anjaneyulu, M.V.L.R., 2016. Estimation of value of travel time for work trips. Transport. Res. Procedia 17 (December 2014), 116–123. https://doi.org/10.1016/j.trpro.2016.11.067.

Balakrishnan, S., Karuppanagounder, K., 2021. Accommodating the heterogeneity in traveller's responsiveness in Safe Route choice experiment – study from India. European Transport - Trasporti Europei 81 (81). https://doi.org/10.48295/ET.2021.81.10.

Basu, A., 2019. Viability assessment of emerging smart urban para-transit solutions: case of cab aggregators in Kolkata city, India. Journal of Urban Management 8 (3), 364–376. https://doi.org/10.1016/j.jum.2019.01.002.

Basu, D., Hunt, J.D., 2012. Valuing of attributes influencing the attractiveness of suburban train service in Mumbai city: a stated preference approach. Transport. Res. Pol. Pract. 46 (9), 1465–1476. https://doi.org/10.1016/j.tra.2012.05.010.

Basu, R., Varghese, V., Jana, A., 2017. Comparison of traditional and emerging paratransit services in Indian metropolises with dissimilar service delivery structures. Asian Transport Studies 4 (3), 518–535. https://doi.org/10.11175/eastsats.4.518.

Beak, Y., Kim, K., Maeng, K., Cho, Y., 2020. Is the environment-friendly factor attractive to customers when purchasing electric vehicles? Evidence from South Korea. Bus. Strat. Environ. 29 (3), 996–1006. https://doi.org/10.1002/bse.2412.

Behl, A., Rathi, P., Ajith Kumar, V.V., 2018. Sustainability of the Indian auto rickshaw sector: identification of enablers and their interrelationship using TISM. Int. J. Serv. Oper. Manag. 31 (2), 137–168. https://doi.org/10.1504/IJSOM.2018.094750.

Belgiawan, P.F., Joewono, T.B., Irawan, M.Z., 2022. Determinant factors of ride-sourcing usage: a case study of ride-sourcing in Bandung, Indonesia. Case Studies on Transport Policy 10 (2), 831–840. https://doi.org/10.1016/j.cstp.2022.02.010.

Bellizzi, M.G., dell'Olio, L., Eboli, L., Mazzulla, G., 2020. Heterogeneity in desired bus service quality from users' and potential users' perspective. Transport. Res. Pol. Pract. 132 (November 2018), 365–377. https://doi.org/10.1016/j.tra.2019.11.029.

Ben-Akiva, M.E., Lerman, S.R., 1985. Discrete Choice Analysis: Theory and Application to Travel Demand. The MIT Press.

Bera, R., Maitra, B., 2022. Commuters' willingness-to-pay for the attributes of plug-in hybrid electric vehicle: a case study in Kolkata, India. Transportation in Developing Economies 8 (1), 1–17. https://doi.org/10.1007/s40890-021-00142-3.

Bhaduri, E., Goswami, A.K., Moeckel, R., 2020. How sustainable is the growth of mass transit system in developing countries - an Indian perspective. Transport. Res. Procedia 48 (2018), 2706–2724. https://doi.org/10.1016/j.trpro.2020.08.244.

Bhat, C.R., 2001. Quasi-random maximum simulated likelihood estimation of the mixed multinomial logit model. Transp. Res. Part B Methodol. 35 (7), 677–693. https://doi.org/10.1016/S0191-2615(00)00014-X.

Bhatia, S.Y., Patil, G.R., Chopadekar, A.D., Sharma, S., 2022. Skywalk facility utilization and factors influencing its use: a case study of Mumbai Metropolitan Region, India. Case Studies on Transport Policy 10 (1), 396–405. https://doi.org/10.1016/j.cstp.2021.12.019.

Bisht, L.S., Ahmed, M.A., 2018. Paratransit system characteristics in mid-size city of silchar, India. Urbanization Challenges in Emerging Economies: Energy and Water Infrastructure; Transportation Infrastructure; and Planning and Financing 757–768. https://doi.org/10.1061/9780784482025.077.

Biswas, R., Pahwa, A., Sheth, M., 2015. The rise of the sharing economy: the Indian Landscape. In: EY (Ernst & Young LLP), vol. 26. Issue 1. http://sharehub.kr/wp-content/uploads/2015/11/e1a7c1d73dfae19dcfa0.pdf.

Campbell, K.B., Rising, J.A., Klopp, J.M., Mbilo, J.M., 2019. Accessibility across transport modes and residential developments in Nairobi. J. Transport Geogr. 74 (November 2018), 77–90. https://doi.org/10.1016/j.jtrangeo.2018.08.002.

Cheranchery, M.F., Maitra, B., 2021. Improving quality of ordinary bus service in Kolkata city: integrating conflicting requirements of users and transit operator. Transport Pol. 111 (July), 17–27. https://doi.org/10.1016/j.tranpol.2021.07.007.

Committee, K., 2017. Report of the committee for determination of the fare structure of taxis and auto rickshaws in Maharashtra state. https://transport.maharashtra.gov.in/Site/Upload/GR/Khatua Committee Report Part 1.pdf.

Dandapat, S., Maitra, B., 2020. Preference heterogeneity in trip makers' perception and policy Issues: a study with reference to bus services in Kolkata. Case Studies on Transport Policy 8 (4), 1504–1517. https://doi.org/10.1016/j.cstp.2020.11.001.

Danesh, A., Velaga, N.R., Ma, W., 2019. User preferences regarding ridesourcing and informal intermediate public transport. CICTP 2019, 6109–6120. https://doi.org/10.1061/9780784482292.524.

Das, D., Kalbar, P.P., Velaga, N.R., 2021a. Framework for comparative evaluation of car-sharing alternatives for urban and suburban regions: case study of Mumbai, India. J. Urban Plann. Dev. 147 (3) https://doi.org/10.1061/(asce)up.1943-5444.0000705.

Das, D., Kalbar, P.P., Velaga, N.R., 2021b. Pathways to decarbonize passenger transportation: implications to India's climate budget. J. Clean. Prod. 295, 126321 https://doi.org/10.1016/j.jclepro.2021.126321.

Das, D., Kalbar, P.P., Velaga, N.R., 2022a. Dynamic stock model based assessment of carpooling in passenger transportation carbon emissions: will avoided trips and material credits help? Sustain. Prod. Consum. 33, 372–388. https://doi.org/10.1016/j.spc.2022.07.007.

Das, D., Kalbar, P.P., Velaga, N.R., 2022b. Role of non-motorized transportation and buses in meeting climate targets of urban regions. Sustain. Cities Soc. 86 (August), 104116 https://doi.org/10.1016/j.scs.2022.104116.

Das, D., Mandal, P., 2021. Comparative evaluation of commuters' preferences and expectations for sharing auto-rickshaw. Case Studies on Transport Policy 9 (4), 1567–1581. https://doi.org/10.1016/j.cstp.2021.08.006.

Deb, S., Ahmed, M.A., 2018. Determining the service quality of the city bus service based on users' perceptions and expectations. Travel Behaviour and Society 12 (July 2017), 1–10. https://doi.org/10.1016/j.tbs.2018.02.008.

Dell'Olio, L., Ibeas, A., Cecin, P., 2011. The quality of service desired by public transport users. Transport Pol. 18 (1), 217–227. https://doi.org/10.1016/j.tranpol.2010.08.005.

Devulapalli, H., Agrawal, G., 2017. Mapping bus transit services in Hyderabad - an illustrative example of the use of open geospatial data. Transport. Res. Procedia 25, 4196–4206. https://doi.org/10.1016/j.trpro.2017.05.369.

Eldeeb, G., Mohamed, M., 2022. Consumers oriented investments in transit service quality improvements: the best bang for your buck. Res. Transport. Econ. 94 (October 2021), 101175 https://doi.org/10.1016/j.retrec.2021.101175.
Ettema, D., Verschuren, L., 2008. Multitasking and value of travel time savings. Transport. Res. Rec.: J. Transport. Res. Board 2010 (1), 19–25. https://doi.org/10.3141/2010–03.
Finn, B., 2012. Towards large-scale flexible transport services: a practical perspective from the domain of paratransit. Research in Transportation Business and Management 3, 39–49. https://doi.org/10.1016/j.rtbm.2012.06.010.
Fleitoukh, A., Toyama, K., 2020. Are ride-sharing platforms good for Indian drivers? An investigation of taxi and auto-rickshaw drivers in Delhi. In: IFIP Advances in Information and Communication Technology, vol. 601. Springer International Publishing. https://doi.org/10.1007/978-3-030-64697-4_10.
Fu, X., Nie, Q., Liu, J., Zhang, Z., Jones, S., 2022. How do college students perceive future shared mobility with autonomous Vehicles? A survey of the University of Alabama students. International Journal of Transportation Science and Technology 11 (2), 189–204. https://doi.org/10.1016/j.ijtst.2021.11.006.
Gao, J., Sha, A., Huang, Y., Hu, L., Tong, Z., Jiang, W., 2018a. Evaluating the cycling comfort on urban roads based on cyclists' perception of vibration. Journal of Cleaner Production Journal. https://doi.org/10.1016/j.jclepro.2018.04.275.
Gao, K., Sun, L., Tu, H., Li, H., 2018b. Heterogeneity in valuation of travel time reliability and in-vehicle crowding for mode choices in multimodal networks. J. Transport. Eng., Part A: Systems 144 (10), 1–10. https://doi.org/10.1061/jtepbs.0000187.
Giansoldati, M., Danielis, R., Rotaris, L., Scorrano, M., 2018. The role of driving range in consumers' purchasing decision for electric cars in Italy. Energy 165, 267–274. https://doi.org/10.1016/j.energy.2018.09.095.
Gohil, D.B., Pesyridis, A., Serrano, J.R., 2020. Overview of clean automotive thermal propulsion options for India to 2030. Appl. Sci. 10 (10) https://doi.org/10.3390/app10103604.
González, R.M., Román, C., Ortúzar, J. de D., 2019. Preferences for sustainable mobility in natural areas: the case of Teide National Park. J. Transport Geogr. 76 (March), 42–51. https://doi.org/10.1016/j.jtrangeo.2019.03.002.
Harding, S.E., Badami, M.G., Reynolds, C.C.O., Kandlikar, M., 2016. Auto-rickshaws in Indian cities: public perceptions and operational realities. Transport Pol. 52, 143–152. https://doi.org/10.1016/j.tranpol.2016.07.013.
Hess, S., Daly, A., Dekker, T., Cabral, M.O., Batley, R., 2017. A framework for capturing heterogeneity, heteroskedasticity, non-linearity, reference dependence and design artefacts in value of time research. Transp. Res. Part B Methodol. 96, 126–149. https://doi.org/10.1016/J.TRB.2016.11.002.
Hess, S., Palma, D., 2019. Apollo: a flexible, powerful and customisable freeware package for choice model estimation and application. Journal of Choice Modelling 32 (June), 100170. https://doi.org/10.1016/j.jocm.2019.100170.
Hess, S., Train, K.E., 2011. Recovery of inter- and intra-personal heterogeneity using mixed logit models. Transp. Res. Part B Methodol. 45 (7), 973–990. https://doi.org/10.1016/J.TRB.2011.05.002.
Hess, S., Train, K.E., Polak, J.W., 2006. On the use of a modified Latin hypercube sampling (MLHS) method in the estimation of a mixed logit model for vehicle choice. Transport. Res. Part B 40 (1), 147–149. https://doi.org/10.1016/j.trb.2004.10.005.
Javid, M.A., Hussain, S., Anwaar, M.F., 2020. Passenger's perceptions on prospects of Qingqi paratransit public transport service in Lahore. Iranian Journal of Science and Technology - Transactions of Civil Engineering 44 (1), 185–195. https://doi.org/10.1007/s40996-019-00273-z.
Javid, M.A., Okamura, T., Nakamura, F., 2015. Public satisfaction with service quality of daewoo urban bus service in Lahore. Journal of the Eastern Asia Society for Transportation Studies 11, 1097–1108. https://doi.org/10.1007/978-3-319-19454-7_132-1.
Jensen, A.F., Thorhauge, M., Mabit, S.E., Rich, J., 2021. Demand for plug-in electric vehicles across segments in the future vehicle market. Transport. Res. Transport Environ. 98 (July), 102976 https://doi.org/10.1016/j.trd.2021.102976.
Johannes du Preez, S., Venter, C., 2022. Mixing the formal with the informal in shared right-of-way systems: a simulation-based case study in Tshwane, South Africa. Case Studies on Transport Policy 10 (1), 145–155. https://doi.org/10.1016/j.cstp.2021.11.012.
Joseph, H.R., Raina, G., Jagannathan, K., 2015. Cost estimates for road congestion in Delhi: Projections and recommendations. In: 2015 7th International Conference on Communication Systems and Networks, COMSNETS 2015 - Proceedings, pp. 1–6. https://doi.org/10.1109/COMSNETS.2015.7098711.
Kalbar, P.P., Das, D., 2020. Advancing life cycle sustainability assessment using multiple criteria decision making. In: Ren, J., Toniolo, S. (Eds.), Life Cycle Sustainability Assessment for Decision-Making: Methodologies and Case Studies. Elsevier, pp. 205–224. https://doi.org/10.1016/B978-0-12-818355-7.00010-5.
Kawasaki, T., Hanaoka, S., Saito, Y., Bandara, Y.M., Nakamichi, K., 2019. Effect of social capital on the life satisfaction of paratransit drivers in Sri Lanka. Transp. Res. Interdiscip. Perspect. 2, 100050 https://doi.org/10.1016/j.trip.2019.100050.
Konbattulwar, V., Velaga, N.R., Jain, S., Sharmila, R.B., 2016. Development of in-vehicle noise prediction models for Mumbai Metropolitan Region, India. J. Traffic Transport. Eng. 3 (4), 380–387. https://doi.org/10.1016/j.jtte.2016.04.002.
Koppelman, F.S., Bhat, C., 2006. A self instructing course in mode choice modeling: multinomial and nested logit models. In: U.S. Department of Transportation Federal Transit Administration, vol. 50. Issue 1. https://www.caee.utexas.edu/prof/bhat/courses/lm_draft_060131final-060630.pdf.
Kraeusel, J., Möst, D., 2012. Carbon Capture and Storage on its way to large-scale deployment: social acceptance and willingness to pay in Germany. Energy Pol. 49, 642–651. https://doi.org/10.1016/j.enpol.2012.07.006.
Kumar, A., Roy, U.K., 2019. E-rickshaws as sustainable last mile connectivity in an urban dilemma: case of Delhi. In: International Conference on Transportation and Development 2019, vol. 2016, pp. 184–195. https://doi.org/10.1061/9780784482582.016.
Kumar, M., Singh, S., Ghate, A.T., Pal, S., Wilson, S.A., 2016. Informal public transport modes in India: a case study of five city regions. IATSS Res. 39 (2), 102–109. https://doi.org/10.1016/j.iatssr.2016.01.001.
Li, H., Gao, K., Tu, H., 2017. Variations in mode-specific valuations of travel time reliability and in-vehicle crowding: implications for demand estimation. Transport. Res. Pol. Pract. 103, 250–263. https://doi.org/10.1016/j.tra.2017.06.009.
Ma, S.C., Xu, J.H., Fan, Y., 2019. Willingness to pay and preferences for alternative incentives to EV purchase subsidies: an empirical study in China. Energy Econ. 81 (x), 197–215. https://doi.org/10.1016/j.eneco.2019.03.012.
Macarthur, E., McKinsey, 2015. Growth within: a circular economy vision for a competitive europe. Ellen MacArthur Foundation 100. Article.
Maitra, B., Dandapat, S., Chintakayala, P., 2015. Differences between the perceptions of captive and choice riders toward bus service attributes and the need for segmentation of bus services in urban India. J. Urban Plann. Dev. 141 (2), 04014018 https://doi.org/10.1061/(asce)up.1943-5444.0000205.
Majumdar, B.B., Mitra, S., 2019. A study on route choice preferences for commuter and non-commuter bicyclists: a case study of Kharagpur and Asansol, India. Transportation 46 (5), 1839–1865. https://doi.org/10.1007/s11116-018-9898-z.
Mani, A., 2010. Why auto-rickshaws matter for India. TheCityFix 1–2. https://thecityfix.com/blog/why-auto-rickshaws-matter-for-india/.
Mani, A., 2012. Case study of the auto- rickshaw sector in Mumbai methodology : thematic areas. In: 3rd Research Symposium on Urban Transport Urban Mobility India 2012, pp. 1–27. http://urbanmobilityindia.in/Upload/Conference/c51d9ce7-5716-4cd0-97b9-5d67a8342dbc.pdf.
Mani, A., Pai, M., Aggarwal, R., 2012. Sustainable urban transport policy in India. In: *WRI* (Issue 1. https://www.wri.org/publication/sustainable-urban-transport-india.
Mani, A., Pant, P., 2012. Review of Literature in India's Urban Auto-Rickshaw Sector: A Synthesis of Findings. https://wrirosscities.org/sites/default/files/Review-Literature-Indian-Urban-Auto-Rickshaw-Sector-EMBARQ-India.pdf.
Meena, S., Patil, G.R., Mondal, A., 2019. Understanding mode choice decisions for shopping mall trips in metro cities of developing countries. Transport. Res. F Traffic Psychol. Behav. 64, 133–146. https://doi.org/10.1016/j.trf.2019.05.002.
Mishra, K., 2018. Over 70 % of All Share Auto Routes in City Are Illegal. Mumbai Mirror. https://mumbaimirror.indiatimes.com/mumbai/cover-story/over-70-of-all-share-auto-routes-in-city-are-illegal/articleshow/65834933.cms.
MMRDA, 2008. Comprehensive Transportation Study for Mumbai Metropolitan Region Itle. https://wricitieshub.org/sites/default/files/pdf_6.pdf.
MMRDA, 2016. Comprehensive Mobility Plan (CMP) for Greater Mumbai. https://portal.mcgm.gov.in/irj/go/km/docs/documents/MCGM Department List/Roads and Traffic/Docs/CMP for Greater Mumbai/Executive Summary/Executive Summary.pdf.
Mohler, B.J., Thompson, W.B., Creem-Regehr, S.H., Pick, H.L., Warren, W.H., 2007. Visual flow influences gait transition speed and preferred walking speed. Exp. Brain Res. 181 (2), 221–228. https://doi.org/10.1007/s00221-007-0917-0.
Muralidhar, S.H., Bossen, C., Mehra, A., O'Neill, J., 2018. Digitizing monetary ecologies: intended and unintended consequences of introducing a financial management app in a low-resource setting. In: Proceedings of the ACM on Human-Computer Interaction, vol. 2. CSCW. https://doi.org/10.1145/3274341.
Nugroho, S.B., Zusman, E., Nakano, R., 2020. Explaining the spread of online taxi services in Semarang, Bogor and Bandung, Indonesia; a discrete choice analysis. Travel Behaviour and Society 20 (April), 358–369. https://doi.org/10.1016/j.tbs.2020.04.008.
OGD, 2019. Projected Population Characteristics as on 1st March 2013: 2001-2026-India. https://data.gov.in/node/96058/datastore/export/xls.
Orme, B.K., 2019. Sample size issues for conjoint analysis. In: Getting Started with Conjoint Analysis: Strategies for Product Design and Pricing Research. Research Publishers LLC, pp. 57–66. https://sawtoothsoftware.com/resources/technical-papers/sample-size-issues-for-conjoint-analysis-studies.
Ortúzar, J. de D., Willumsen, L.G., 2011. Modelling Transport. *Modelling Transport*. https://doi.org/10.1002/9781119993308.
Panda, R., Verma, S., Mehta, B., 2015. Emergence and acceptance of sharing economy in India. Int. J. Online Market. 5 (3), 1–17. https://doi.org/10.4018/IJOM.2015070101.
Pandit, D., Sharma, D., 2022. Expected service dimensions and service levels for paratransit considering future mobility needs in emerging countries. Transport. Res. Pol. Pract. 162 (May), 1–13. https://doi.org/10.1016/j.tra.2022.05.021.
Priye, S., Manoj, M., 2020. Exploring usage patterns and safety perceptions of the users of electric three- wheeled paratransit in Patna , India. Case Studies on Transport Policy 8 (1), 39–48. https://doi.org/10.1016/j.cstp.2020.01.001.
Priye, S., Manoj, M., Ranjan, R., 2021. Understanding the socioeconomic characteristics of paratransit drivers and their perceptions toward electric three-wheeled rickshaws in Delhi, India. IATSS Res. https://doi.org/10.1016/j.iatssr.2021.03.002 xxxx.
Rahman, F., 2022. Exploring paratransit service quality based on low-income women's perception: a case study in Dhaka city by structural equation model (SEM). IATSS Res. 46 (2), 181–192. https://doi.org/10.1016/j.iatssr.2021.11.009.
Rajkot, C.M.P., 2014. Low-Carbon Comprehensive Mobility Plan Rajkot. https://wedocs.unep.org/bitstream/handle/20.500.11822/31362/LCCMP.pdf?sequence=1&isAllowed=y.
Rastogi, R., Rao, K.V.K., 2003. Defining transit accessibility with environmental inputs. Transport. Res. Transport Environ. 8 (5), 383–396. https://doi.org/10.1016/S1361-9209(03)00024-5.
Reddy, K.S., Aravindhan, S., Mallick, T.K., 2017. Techno-economic investigation of solar powered electric auto-rickshaw for a sustainable transport system. Energies 10 (6), 1–15. https://doi.org/10.3390/en10060754.

Rink, B., 2022. Capturing amaphela: negotiating township politics through shared mobility. Geoforum 136 (June 2020), 232–241. https://doi.org/10.1016/j.geoforum.2020.06.010.

Rose, J.M., Bliemer, M.C.J., 2013. Sample size requirements for stated choice experiments. Transportation 40 (5), 1021–1041. https://doi.org/10.1007/s11116-013-9451-z.

Rukmini, S., 2015. How much money do we actually need?. The Hindu, pp. 1–4. https://www.thehindu.com/opinion/blogs/blog-datadelve/article6986491.ece.

Sadhukhan, S., Banerjee, U.K., Maitra, B., 2016. Commuters' willingness-to-pay for improvement of transfer facilities in and around metro stations – a case study in Kolkata. Transport. Res. Pol. Pract. 92, 43–58. https://doi.org/10.1016/j.tra.2016.07.004.

Santana Palacios, M., Cochran, A., Bell, C., Hernández Jiménez, U., Leshner, E., Trejo Morales, F., Chatman, D.G., 2020. Bus rapid transit arrives in Barranquilla, Colombia: understanding a changing landscape through residents' travel experiences. Travel Behaviour and Society 21 (April), 131–139. https://doi.org/10.1016/j.tbs.2020.06.003.

Schmucker, U., Dandona, R., Kumar, G.A., Dandona, L., 2011. Crashes involving motorised rickshaws in urban India: characteristics and injury patterns. Injury 42 (1), 104–111. https://doi.org/10.1016/j.injury.2009.10.049.

Shafizadeh-Moghadam, H., Helbich, M., 2015. Spatiotemporal variability of urban growth factors: a global and local perspective on the megacity of Mumbai. Int. J. Appl. Earth Obs. Geoinf. 35 (PB), 187–198. https://doi.org/10.1016/j.jag.2014.08.013.

Sharma, D., Pandit, D., Bose, T., 2020. Determination of service quality attributes based on user perception for paratransit services in developing country like India. Transport. Res. Procedia 48 (2019), 3577–3594. https://doi.org/10.1016/j.trpro.2020.08.093.

Shirgaokar, M., 2019. Operationalizing gendered transportation preferences: a psychological framework incorporating time constraints and risk aversion. Transport Pol. 75 (December 2018), 10–18. https://doi.org/10.1016/j.tranpol.2018.12.010.

Shlaes, E., Mani, A., 2014. Case study of autorickshaw industry in Mumbai, India. Transport. Res. Rec. 2416 (2416), 56–63. https://doi.org/10.3141/2416-07.

Sweet, M.N., 2021. User interest in on-demand, shared, and driverless mobility: evidence from stated preference choice experiments in Southern Ontario. Travel Behaviour and Society 23 (November 2020), 120–133. https://doi.org/10.1016/j.tbs.2020.12.003.

Tanaka, M., Ida, T., Murakami, K., Friedman, L., 2014. Consumers' willingness to pay for alternative fuel vehicles: a comparative discrete choice analysis between the US and Japan. Transport. Res. Pol. Pract. 70 (2014), 194–209. https://doi.org/10.1016/j.tra.2014.10.019.

TERI, 2015. Environment Status Report of Mumbai Metropolitan Region (MMR), vol. 707. https://www.mmreis.org.in/images/research/Environmental Status Report for Mumbai Metropolitan Region-ilovepdf-compressed.pdf.

Train, K.E., 2009. Discrete Choice Methods with Simulation. Cambridge university press. https://doi.org/10.1080/07474938.2014.975634.

Trivedi, S., Prasad, R., Mishra, A., Kalam, A., Yadav, P., 2020. Current scenario of CNG vehicular pollution and their possible abatement technologies: an overview. Environ. Sci. Pollut. Control Ser. 27 (32), 39977–40000. https://doi.org/10.1007/s11356-020-10361-7.

Varghese, V., Jana, A., 2018. Impact of ICT on multitasking during travel and the value of travel time savings: empirical evidences from Mumbai, India. Travel Behaviour and Society 12 (December 2017), 11–22. https://doi.org/10.1016/j.tbs.2018.03.003.

Wang, C., Sun, J., Russell, R., Daziano, R.A., 2018. Analyzing willingness to improve the resilience of New York City's transportation system. Transport Pol. 69 (May), 10–19. https://doi.org/10.1016/j.tranpol.2018.05.010.

Weicker, T., 2022. Marshrutka (in)formality in southern Russian cities and its role in contentious transport policies. Geoforum 136 (June 2020), 262–272. https://doi.org/10.1016/j.geoforum.2020.08.015.

Wheeler, B., Braun, J., 2022. Package 'AlgDesign.'. https://cran.r-project.org/web/packages/AlgDesign/AlgDesign.pdf.

Wisutwattanasak, P., Jomnonkwao, S., Se, C., Ratanavaraha, V., 2022. Influence of psychological perspectives and demographics on drivers' valuation of road accidents: a combination of confirmatory factor analysis and preference heterogeneity model. Behav. Sci. 12 (9) https://doi.org/10.3390/bs12090336.

Wongwiriya, P., Nakamura, F., Tanaka, S., Ariyoshi, R., Miura, S., 2020. The role of paratransit to support sustainable transportation: case study of Khon kaen city, Thailand. Transport. Res. Procedia 48 (2019), 2656–2670. https://doi.org/10.1016/j.trpro.2020.08.247.

WPR, 2023. India population 2023 (live). World Population Review. https://worldpopulationreview.com/countries/india-population.

Wright, S., Emele, C.D., Fukumoto, M., Velaga, N.R., Nelson, J.D., 2014. The design, management and operation of flexible transport systems: comparison of experience between UK, Japan and India. Res. Transport. Econ. 48, 330–338. https://doi.org/10.1016/j.retrec.2014.09.060.