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Article

Assessing the Factors Impacting Transport Usage of Mobility App Users in the National Capital Territory of Delhi, India

Sanjay Gupta [1] and Kushagra Sinha [1,*]

[1] Department of Transport Planning, School of Planning and Architecture, 4, Block-B, Indraprastha Estate, New Delhi, India; SG: drsgupta19@gmail.com; KS: kush.spab@gmail.com
* Correspondence: kush.spab@gmail.com

Abstract: Smartphone-based mobility apps enable users to make informed transportation decisions, offering instant access to transport-related information. This development has created a smartphone-enabled ecosystem of mobility services in developed countries while it is slowly picking up pace in the global south, which can contribute towards the decarbonization of urban transport. Work on this has already started in India, and there is considerable evidence indicating the profound impact of these apps on the perceived utility and usage of transport modes, with far-reaching implications for sustainable development goals (SDGs). However, for most users, the use of smartphone apps is a novel trend, and the knowledge of the impacts of usage of existing apps on the usage pattern of transport modes by various user groups is essential for positioning new consolidated app-based services soon. Against this backdrop, the present study uses latent class cluster analysis to empirically investigate the impacts of mobility apps on transport mode usage patterns in Delhi by classifying users into latent classes based on socioeconomic characteristics, attitudes/preferences, smartphone app usage, and mode usage pattern. The characteristics of the latent class and factors affecting the individual's probability of being classified to these cluster have been discussed, along with some measures to encourage app-based mobility for each cluster.

Keywords: App Usage; Transport Mode Usage; Latent Class Cluster Analysis; Multimodality; Environment

1. Introduction

The social and economic progress of society is strongly influenced by the transport sector. Today, it would not be easy to live without modern transportation services. Almost all human activities are connected to this sector, including but not limited to connecting students to universities, schools, and other places of education, connecting employees to the workplace, connecting buyers and sellers, and facilitating social and recreational activities. However, as fossil fuels mainly fuel the sector, it has also become responsible for environmental issues, including emissions of greenhouse gases (GHGs). Around 25% of global CO_2 emissions came from the transport sector in the year 2016, a 71% increase from 1990, and roads account for 75% of all transport emissions [1].

India's urbanisation and rapid economic expansion have significantly increased the demand for mobility services [2]. However, as passenger traffic increased significantly, the number of private cars rather than the use of public transport increased [3]. One of the significant drivers of climate change and its consequences on urban sustainability is also the rapid increase in privately owned motorized transport, the provision of road infrastructure and the lack of high-quality integrated mobility services in Indian cities. Following the United Nation's Paris Agreement of 2015, India announced an Intended Nationally Determined Contribution (INDC) for reducing GHG emissions from India's GDP by 33-35% by the year 2050 [4] and low-carbon mobility is critical to achieving that [5].

Policymakers are considering comprehensive measures, including technological advances and policy measures, as efforts to achieve low-carbon transport and mobility. This

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includes encouraging a shift from private vehicles to mass transit and non-motorised transport, while simultaneously reducing the demand for travel through travel demand management measures. Technology plays a key role in this, primarily through recent advances in information and communication technology (ICT) and its applications in transport sector [6]. In the last decade, ICT has become much more available, especially in the form of mobile phones. According to the latest figures, the use of mobile phones has grown exponentially, and India has 85 mobile phone connections for every 100 individuals [7]. These mobile phones have also evolved from an essential communication tool to trusted information, communication, search, and entertainment device known as a smartphone.

Smartphone applications or "apps" are capable of providing quick access to previously unavailable transport-related information, including real-time data, in some cases, to enable users to make informed mobility decisions. The way people use smartphone apps for travel is constantly evolving. Smartphone users are increasingly using apps for various transportation applications. More and more people use their smartphones to start a trip, direct a trip, check the departure time of the next bus, train, or subway, hail a taxi, or use the services of an app-based taxi aggregator. In developed countries, this has created a smartphone-enabled ecosystem of mobility services called Mobility-as-a-Service (MaaS) – a platform that combines different transportation modes and services into a single app. An example is 'Whim' in Helsinki (Finland), where travellers can plan and pay for trips across a variety of modes including public transport, bike-share, taxis, carpool/carshare, etc. The need to toggle between apps has been eliminated, and everything is sitting right there when one opens Whim, making it highly convenient and easy to use. This single app has driven users towards multimodality, and they are shifting towards sustainable mobility patterns [8]. Such platforms have either already been deployed or are under trial in many cities across the world.

Work on a smartphone enabled connected mobility platforms has already started in India, and the Ministry of Housing and Urban Affairs (MoHUA) of Government of India, in collaboration with industry partners are working to establish a framework to introduce smartphone-enabled connected mobility platforms in Indian cities for integrating all forms of shared transportation through a single app with multiple functions, including route/mode choices and payment gateways [9]. Owing to rapidly increasing internet and smartphone penetration in all the regions of the country as a result of lowering of the costs of data and handsets, along with other flagship government projects like 'Smart Cities Mission' [10], which aims to develop 100 prominent Indian cities that are meant to procure and integrate the most advanced technologies that the industry can provide to create a highly connected and technology-friendly infrastructure [11] and 'Digital India' [12] for improving access to the internet in all urban and rural areas, it is not going to be long when use cases based on these platforms start emerging in Indian cities.

However, the market for smartphones and their applications is still developing, and it is unclear how they will affect everyday mobility patterns of users in the future with these continuous changes and improvements [13]. Therefore, examining the relationship between the usage of smartphone-based transport apps and transport system usage may provide insights into the potential impact of smartphone app usage on people's transport preferences. Such research could aid in policy development measures for smartphone-related travel enhancements and alternatives, such as carpooling, shared mobility, etc. [14], further contributing towards a low-carbon future of urban transport.

Modern research has shown that the use of ICT devices has changed daily activities and travel decisions, such as time of activity, start time, destination selection, selection of transportation mode, selection of route, etc. [15 - 17]. The versatility of smartphone apps is changing the way people travel every day. People can use various smartphone apps for work, shopping, banking, etc., instead of physically travelling. Smartphone apps can also become a popular source of information about various places and attractions, local festivals, and community events, leading to trips to new places and attending social gatherings. Smartphone users can use reviews and ratings for new places to decide whether to visit them. Users may even get encouraged to participate in community events due to readily available information about local activities [14]. With the advent of smartphone-based shared mobility solutions, users now also have various transport options to cater to these new mobility requirements.

In this context, the objectives of this study are twofold. First, it attempts to probabilistically classify smartphone users into groups with similar transport usage patterns using a rich set of covariates, including socioeconomic characteristics, smartphone app usage patterns and attitudes/preferences, while maximizing the diversity of these patterns between groups. Second, it also seeks to analyse these mentioned covariates as factors which affect the probabilities of individuals to belong to these clusters.

2. Materials and Methods

2.1. Case Study

The National Capital Territory (NCT) of Delhi has been chosen. It has strong arguments for being considered a Case Study, including the operation of nearly all platforms and aggregators, the presence of important policymakers and their ministries, and a variety of travel options, including the metro, rails, public buses, private buses, auto-rickshaws, and informal three-wheelers. As per the Census of India (2011), more than 18.9 million people [18] live in 1,483 Sq. km (11,320 persons/sq.km) and are mostly urban (97.5%). The per capita income is relatively higher in Delhi (INR 4,01,982) compared to other Indian cities and ranks third after the provinces of Sikkim and Goa [19]. It also has a literacy rate of 86.2%. The telecommunications network is well-established in Delhi. It has high teledensity, with 52.4 million wireless subscribers [7]. This makes this city the perfect location for introducing Smartphone apps for various travel requirements like deciding when to depart, mode choice online shopping, etc. [20], and the city currently has several such platforms (Table 1).

Table 1. Types of Smartphone Apps for Travel Needs available in Delhi

App Type	Travel Requirements	Examples
Travel Apps for Trip Planning Activities	Deciding Departure Time	Map Services (Google, Apple, etc.)
	Deciding Trip Destination	BookMyShow, Zomato, etc
	Selecting Mode of Transport	Map Services (Google, Apple, etc.), One Delhi App, etc.
	Selection of Route	Map Services (Google, Apple, etc.)
	Communicating & Coordinating	Social Network Services, Chat Services, etc.
	Online Tasks	e-Tickets (IRCTC, BookmyShow, PayTM, etc.), smartcard recharge (Paytm, Phonepay, etc.)
Travel Apps for other Travel impacting purposes	Reserving Taxis/Cabs	Ola, Uber, Rapido, Zoomcar, Volar, etc.
	Checking Bus/Metro Schedules	Map Services (Google, Apple, etc.), One Delhi App, etc.
	Navigation	Map Services (Google, Apple, etc.)
	Online Shopping	Shopping (Amazon, Myntra, etc.) Food Delivery (Swiggy, Zomato, etc.) and Quick Grocery Delivery (Swiggy Instamart)
	Virtual Activities	Banking (UPI, Internet Banking, etc.), Education (EdX, Byjus, Unacademy, etc.) and Utilities (Urban Company).
	Scheduling Meetups	Social Network Services, Chat Services, Video Conferencing (Facebook, WhatsApp, Zoom, etc.)

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Source: Authors

2.2. *Data and Variables*

The primary data used in this study has been collected through an online survey of smartphone users. The interviews were conducted between September 2021 and December 2021, and a representative sample of 530 people for NCT Delhi was collected via a stratified random sampling technique. The following are the components of the questionnaire –

- **Transport Usage:** As previously mentioned, Delhi has a variety of travel options, but four main types of systems were considered in this study: private vehicles (including four- and two-wheeled motor vehicles), public transport (including bus and metro services), intermediate public transport or "IPT" services (including autorickshaws and battery-powered rickshaws) and app-based shared mobility services. Respondents were asked questions about their propensity of usage of the aforementioned modes of transport on a Likert scale with responses: Never, Rarely, Sometimes, Often and Always.
- **Socio-economic Data:** Personal level details like Gender, Age Group (users below 18 years of age have not been considered in this study), Educational Qualification and Years of Smartphone use; and Household level details including household composition (with or without children below 18 years of age), monthly household income, four-wheeler ownership and two-wheeler ownership were recorded. The personal and household-level socioeconomic information has been recorded as categorical choices.
- **Smartphone App Usage:** Responses were collected from smartphone users concerning their frequency of use of smartphone apps for activities associated with trip planning like deciding departure time for a trip, deciding destinations, selecting transportation mode, performing essential tasks online instead of travelling to a designated location and, communicating and coordinating, and other travel impacting purposes such as navigation, checking the schedule of public transport, online shopping, etc. Information was collected on a Likert Scale, with responses: Never, Rarely, Sometimes, Often and Always.
- **Attitudes and Preferences:** The dataset includes respondents' degrees of agreement with 12 statements about attitudes and preferences on a Likert-type, with responses: Strongly disagree, Slightly Disagree, Neutral, Slightly Agree and Strongly agree.

2.3. *Methods*

2.3.1. Chi – Square Test of Association

The test has been performed between socio-economic parameters and usage frequency of the transport modes for testing association between them. SPSS software package has been used to perform this analysis and apart from Gender (Table 2), all the personal level and household level variable have shown a strong association with frequency of use of transport modes.

Table 2. Chi - Square test for Gender and Frequency of Use of Transport Systems

Frequency of Use for	**Gender**

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	Pearson Chi – Square: Asymptotic Significance (2 sided)	Cramer's V
Private Vehicle	Less than 0.01	0.234
Public Transport	0.874	-
Intermediate Public Transport	Less than 0.01	0.214
App – based Cab Services	Less than 0.01	0.168

Apart from the frequency of use of public transport, Gender has a significant relationship ($p < 0.01$) with frequency of use of modes. Cramer's V, a measure of the effect size for the chi-square test of independence, has been used to assess the strength of association between gender and frequency of use of transport systems for the significant relationships, that is, it measures the degree to which the two categorical fields are associated [21]. Here, measurement of effect size in each significant relationship is close to 0.2 which means that although the results are statistically significant, the fields are only weakly associated [22].

2.3.2. Exploratory Factor Analysis (or EFA)

EFA has been used as a variable reduction technique for the statements recording attitudes and preferences and accounts for the common variance among them [23]. SPSS software package has been used to perform this analysis. Statement having low factor loading (less than 0.4 in this study) should be considered [24]. Table 3 shows the statements along with the estimated factor loadings.

Table 3. Statements for assessing Attitudes & Preferences of Smartphone Users towards Choice of Transport

	Statements	Factor Loadings
1.	It does not matter what type of mode I use, if it is suitable for my travel needs.	0.4
2.	I often compare various travel options and modes of transportation before starting a trip.	0.7
3.	To improve transport, it is essential to be able to easily combine different modes of transport, such as buses, cars, bicycles, or car sharing.	0.6
4.	I am ready to try new ways and systems to travel	0.6
5.	It is uncomfortable to ride public transport with strangers	0.6
6.	Public transport lacks in cleanliness	0.5
7.	Use of public transport is important to preserve the environment	0.5
8.	I prefer to use public transport and/or share my rides for reducing travel costs.	0.8
9.	I would prefer to enjoy the convenience of a car without owning it.	0.6
10.	I like privacy offered by a private car or bike	0.7
11.	People like me only use privately owned cars and/or bikes	0.6
12.	If there was a cheaper alternative, I would reduce my private vehicle usage	0.6

It can be observed that none of the statements have factor loading less than 0.4 and can be considered for further analysis. Data suitability for EFA was investigated using Kaiser-Meyer-Olkin (KMO) model fit measures, along with Bartlett's test of sphericity [24]. A KMO of 0.936 has been obtained, showing good sample adequacy [25], and the Bartlett's test is less than 0.001 indicating good relations between indicators for the EFA.

2.3.3. Latent Class Cluster Analysis (or LCCA)

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LCCA has been used to probabilistically classify smartphone app users into traveller groups, each characterised by somewhat similar patterns of mode use while also maximising their heterogeneity across groups. The model classifies individuals in different clusters based on unobserved (latent) variables that describes their responses for a set of observed indicators [26]. Compared to more simple techniques, this analytical approach has several advantages for identifying multimodal travel behaviours. As travel multimodality cannot be simply reduced to a one-dimensional measure like HHI or Shannon's Entropy, LCCA aims to quantify multimodality as a whole rather than creating a single (composite) index. Instead, it classifies individuals into latent classes on the basis of multiple indicators that reflect each class's unique mode usage patterns. Second, this method evaluates individual's probability of being classified to various latent classes, in contrast to deterministic classification approaches. Each of these classes displays a unique profile that includes the average frequency of use for the various modes. In particular, this is the mean of a set of sample-wide probability-weighted indicator variables [27].

The model includes two sub-models which are simultaneously estimated. A multinomial logit model is used in one sub-model to estimate the probability that the individual 'i' (with the covariates 'x_i') belongs to the latent class 'c'. The other sub-model estimates specific means and standard deviations for 'J' indicators for each class, 'y_{ij}' (j=1, 2, 3, … , J) or arrayed into the vector 'y_i' that is the monthly frequencies of transport mode usage, and also assumes that the indicators will have a normal distribution. Equation below represents the entire model [28].

$$P(y_i|x_i) = \sum_{c=1}^{C} P(c|x_i) \prod_{j=1}^{J} P(y_{ij}|c) \quad (1)$$

The results include two sets of estimations for parameter: the active covariate coefficients specific to the class, as well as averages and standard deviations of the indicators specific to the class. The statistical significance of a given covariate in a multinomial logit model setting determines whether it accounts for the probability of a commuter's membership in a particular class. The relationships between the indicators, the active and inactive variables, and the latent structure of mobility styles are shown in Figure 1.

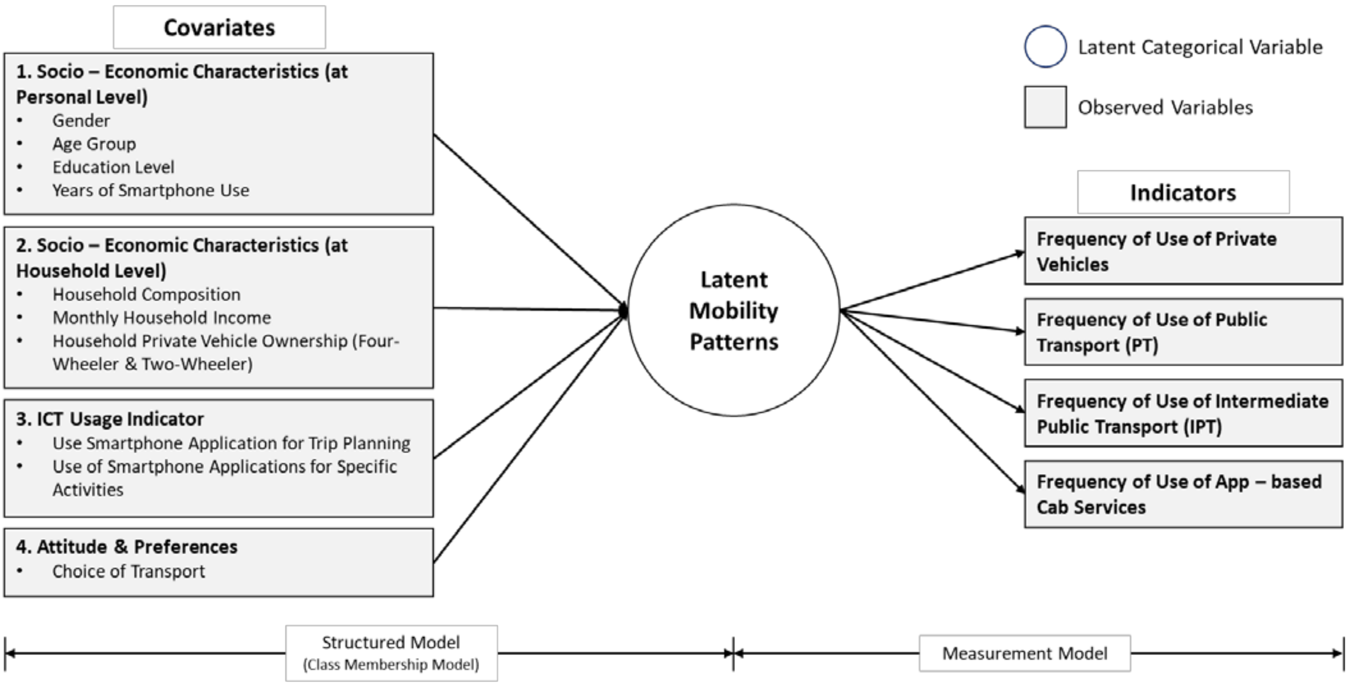

Figure 1. Representation of the LCCA with covariates and indicators

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The LCCA has been performed using the Latent Gold software package, which performs this analysis within an interactive graphics environment [29]. Gender has been considered an inactive covariate because of weak association frequency of use of transport systems. Also, the value of factor loading for first statement – "It does not matter what type of mode I use, if it is suitable for my travel needs." is approximately 0.4 and it has also been considered an inactive covariate. These covariates have been coded such that they do not directly contribute to the LCCA model but are still used as analysis parameters.

3. Results

The model has been executed in Latent Gold with a different number of specified latent classes, and the best among those models has been determined by information criteria. The software reports useful criterion (Table 4) like the Akaike Information Criterion (or AIC) and the Bayesian Information Criterion (or BIC) (for formulas, see [30-32]). A better model fit is associated with low values for these criteria.

Table 4. Evaluation of Information criterion for models with a different number of classes

Number of Classes	**1**	**2**	**3**	**4**
AIC	36005	35562	**35245**	35553
BIC	38120	37677	**37360**	37668

The three-class solution has been chosen as the best after analysing several alternatives, based on lower AIC and BIC information criterion values. Out of all the samples, 41% were classified in Cluster-1, 34% in Cluster-2 and the remaining 25% in Cluster-3.

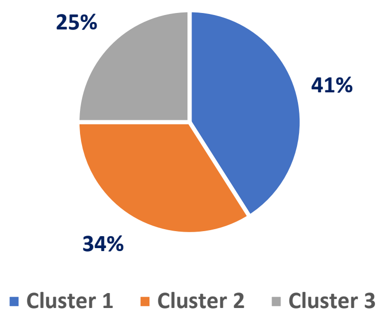

Figure 2. Percentage share of samples classified into various clusters by LCCA model

3.1. *Cluster–wise Transport Mode Usage*

Figure 3 shows the frequency profiles for using various modes of transport considered in the study for the respondents clustered into the three latent class clusters. The darker shades represent higher usage of transport modes.

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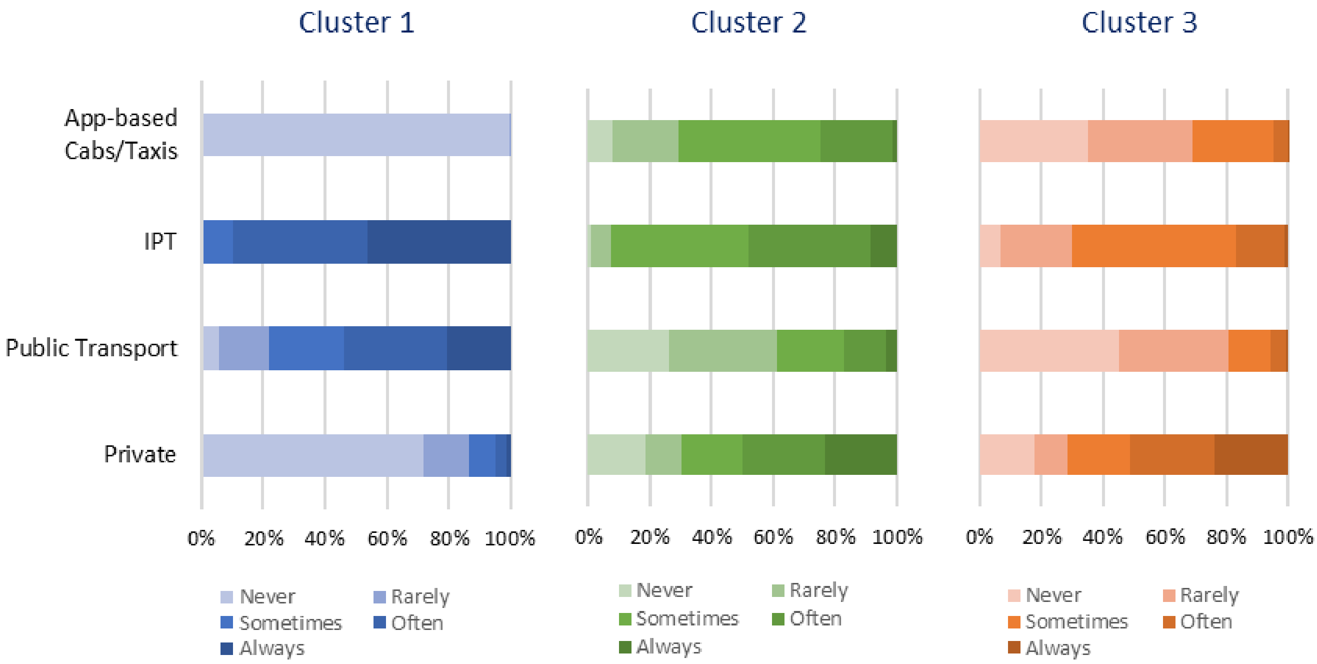

Figure 3. Cluster-wise Transport Mode Usage Pattern

It has been observed that the respondents classified in cluster 1 show very high reliance on public and intermediate public transport, less dependence on private vehicles and no usage of app-based cabs/taxis. In contrast, the ones classified in Cluster 2 show a significant dependence on all modes of transport. Finally, respondents in Cluster 3 show higher reliance on private vehicles. Thus, the three latent classes can be named as follows–

- Cluster 1: PT & IPT Users
- Cluster 2: Multimodal Travellers
- Cluster 3: Private Vehicle User

All the active and inactive covariates can now be classified under these latent classes as per the LCCA model.

3.2. *Cluster Profile for App Usage*

Figure 4 shows the profile for frequency of smartphone app usage for trip planning activities by respondents clustered into the three latent classes. Although most respondents reported a very high dependence on app usage for communication and coordination, respondents who stated 'Never' to 'Sometimes' for all the trip planning purposes have high probability of being classified as PT & IPT user. On the other hand, those who stated 'Often' to 'Always' for all purposes have high probability of being classified as multimodal travellers. The respondents classified private vehicle users have stated varied responses between 'Rarely' and 'Often'.

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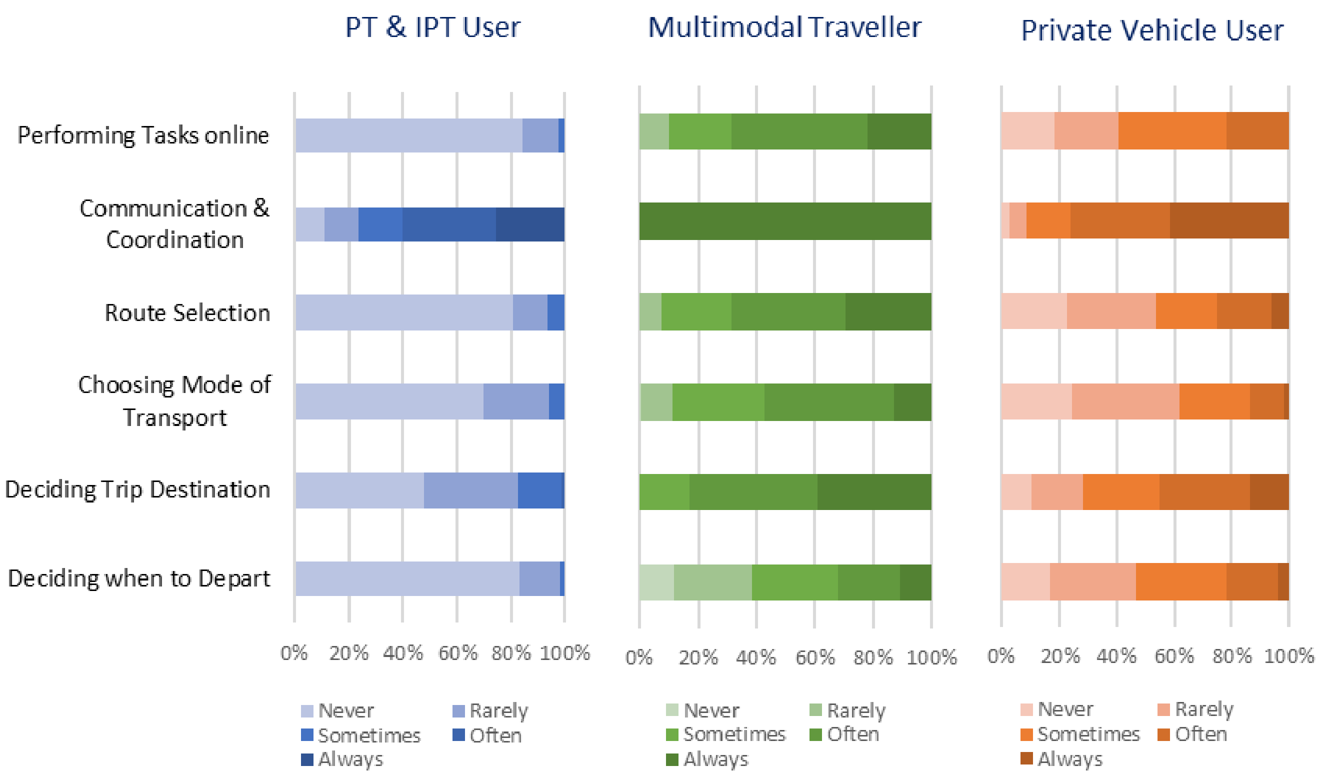

Figure 4. Cluster probabilities of respondents based on Usage of Trip Planning Activities

Following is the cluster-wise app usage pattern for trip planning purposes–

- **PT & IPT User:** As stated, respondents show high dependence on communication and coordination as most stated that they Always or Often use them. Most respondents have stated that they never use smartphone apps to decide when to depart, choose mode of transport, make route selections, and perform tasks online. In comparison, a relatively higher proportion of users have stated that they use apps to decide trip destinations on rare occasions.
- **Multimodal Traveller:** Respondents show very high dependence on communication and coordination as all of them stated that they Always use them. To decide trip destinations, choose a mode of transport, make route selection and perform tasks online, most respondents have stated that they often or always use smartphone apps. For deciding when to depart, the largest share of respondents stated that they use apps sometimes.
- **Private Vehicle user:** Respondents show high dependence on apps for communication and coordination. To decide when to depart, choosing a mode of transport and performing tasks online, most users show medium dependence on app usage, and a large proportion reported ‘Rarely’ to ‘Sometimes’. For deciding, trip destinations majority of respondents stated that they use apps ‘Sometimes’ or ‘Often’.

Figure 5 shows the profile for frequency of smartphone app usage for other travel-impacting purposes by the respondents clustered into the three latent classes. Although most respondents reported a very high dependence on app usage for scheduling meetups using social networking apps, respondents who stated ‘Never’ to ‘Sometimes’ have a higher probability of getting classified as PT & IPT users for all the trip planning purposes. On the other hand, those who stated ‘Often’ to ‘Always’ have high probability of being classified as multimodal travellers. The respondents classified as private vehicle users have varied responses between ‘Rarely’ and ‘Often’.

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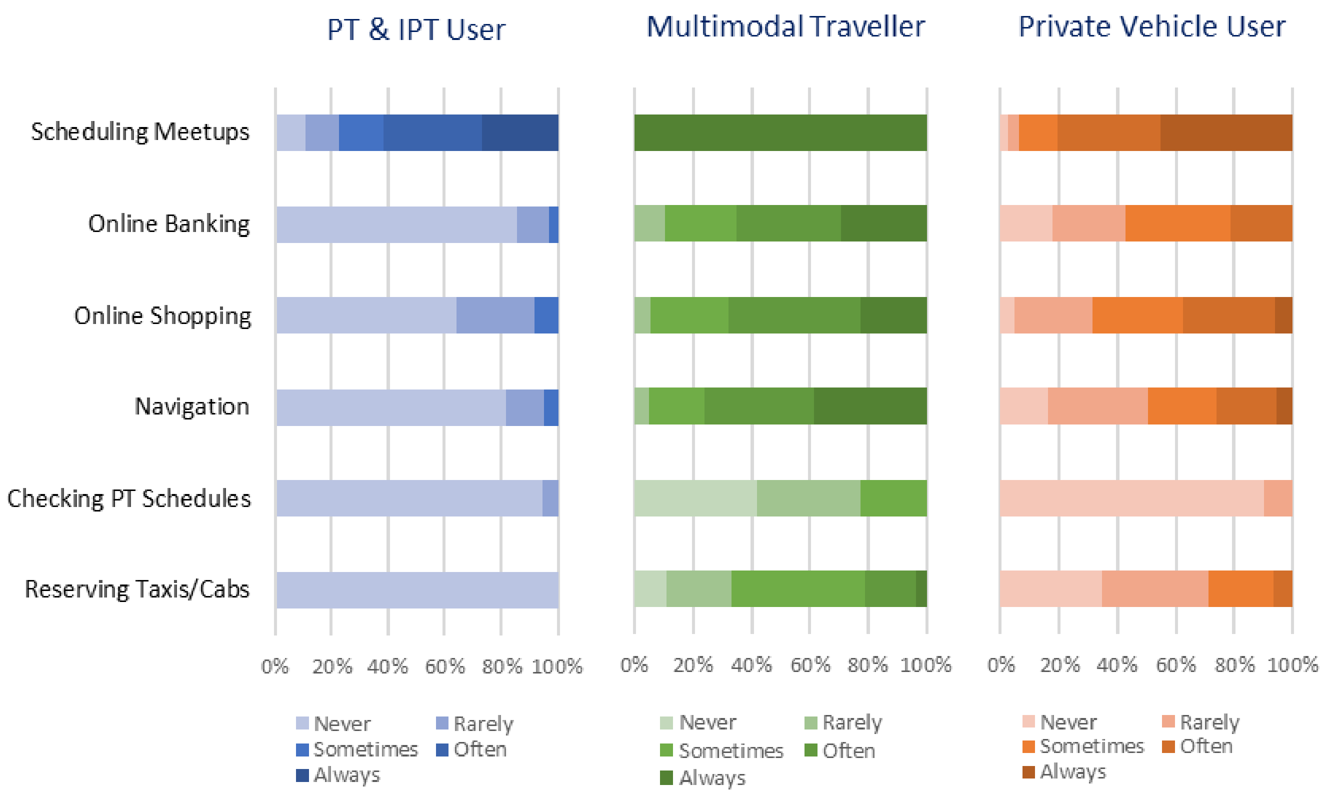

Figure 5. Cluster probabilities of respondents based on Usage of other Travel Impacting Purposes

Following is the cluster-wise app usage pattern for other travel-impacting purposes–

- **PT & IPT User:** The respondents in this cluster stated that they never use apps for reserving taxis/cabs. As stated, respondents show high dependence on scheduling meetups as most stated that they 'Always' or 'Often' use them. Most respondents have said they never use smartphone apps for navigation and online banking. In comparison, a relatively higher proportion of users have stated that they use apps for online shopping on rare occasions. The respondents stated the least dependence on the purpose of checking PT schedules.
- **Multimodal Traveller:** Respondents show very high dependence on scheduling meetups as they all stated that they 'Always' use them. For reserving taxis/cabs, most respondents have stated that they sometimes use smartphone apps. However, less dependence on apps is observed for checking PT schedules, but it is still more than other clusters. For navigation, online shopping and online banking, a large share of respondents stated high reliance on apps.
- **Private Vehicle user:** Most respondents show limited dependence on apps for reserving taxis/cabs, which is more than Cluster 1. To decide when to depart, choosing a mode of transport and performing tasks online, most users show medium dependence on app usage, and a large proportion reported 'Rarely' to 'Sometimes'. For deciding trip destinations, most respondents stated that they use apps 'Sometimes' or 'Often'.

From the analysis of app usage patterns for both types of purposes, it can be inferred that users with lower dependence on apps have high probability of getting classified in Cluster 1 as PT & IPT User, ones with higher dependence on apps have high probability

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of getting classified in Cluster 2 as Multimodal Traveller and ones with medium dependence on apps have high probability of getting classified in Cluster 3 as Private Vehicle User.

3.3. *Class Memberships*

In addition to depicting the three latent class clusters of travellers, an attempt has been made to analyse the mentioned covariates as factors which affect the probabilities of individuals to belong to these clusters.

3.3.1. Socioeconomic Characteristics

Table 5 shows the probabilities of respondents to be classified in a cluster depending upon their socioeconomic characteristics.

Table 5. Cluster probabilities of respondents based on Socioeconomic characteristics

Socioeconomic Characteristics	**Latent Classes (Clusters)**		
	Cluster 1: PT & IPT User	**Cluster 2: Multimodal Traveller**	**Cluster 3: Private Vehicle User**
Gender <Inactive>			
Male	**41.5%**	33.8%	24.7%
Female	**41.6%**	33.7%	24.7%
Age Group			
18 to 24 Years	40%	**60%**	0%
25 to 34 Years	40%	**60%**	0.0%
35 to 44 Years	**40%**	20%	**40%**
45 to 54 Years	40%	0%	**60%**
55 to 64 Years	44%	0%	**56%**
65 Years & above	**60%**	0%	40%
Educational Qualification			
High (undergraduate degree or more)	4.4%	**71.7%**	23.9%
Medium (high school education)	27.7%	**36.5%**	**35.8%**
Low (less than high school education)	**81.7%**	0%	18.3%
Experience with Smartphone Use			
Less than 1 Year	**100%**	0%	0%
1 to 3 Years	**100%**	0%	0%
3 to 5 Years	**86.9%**	13.1%	0%
More than 5 Years	14.2%	**47.9%**	37.9%
Household Composition			
With Children below 18 Years	35.9%	**36.3%**	27.9%
Without Children below 18 Years	**46.6%**	31.5%	21.9%
Monthly Household Income			
Less than INR 5,000	**100%**	0%	0%
INR 5,000 to 20,000	**100%**	0%	0%
INR 20,000 to 50,000	7.5%	**49.1%**	43.4%
INR 50,000 to 100,000	0%	**49.1%**	**50.9%**
More than INR 100,000	0%	**70.8%**	29.2%

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Socioeconomic Characteristics	Latent Classes (Clusters)		
	Cluster 1: PT & IPT User	Cluster 2: Multimodal Traveller	Cluster 3: Private Vehicle User
Four-Wheeler Ownership			
None	**91.8%**	0%	8.2%
One	3.5%	**47.6%**	**48.9%**
Two	0%	38.2%	**61.8%**
Three or More	0%	26.3%	**73.7%**
Two-Wheeler Ownership			
None	**89.6%**	0%	10.4%
One	25%	**36.1%**	**38.9%**
Two or More	2.3%	40.2%	**57.6%**

The bold values represent the highest value for each row

Following are the characteristic-wise cluster probabilities –

- **Gender:** It can be observed that for both male and female respondents, the probability of getting classified as a PT & IPT user (41.5% and 41.6% respectively) is slightly higher than multimodal traveller and significantly higher than private vehicle user.
- **Age Group:** Younger Users (18 to 34 years) have a higher probability (60%) of getting classified as a multimodal traveller and no probability of getting classified as private vehicle users. The respondents of the 35 to 44 years age group have equal probability (40% each) of getting PT & IPT users or private vehicle users. Respondents of older age groups of 45 to 54 years and 55 to 64 years have a higher probability (60% and 56% respectively) of getting classified as private vehicle users and respondents of age 65 years and above have a high probability (60%) of getting classified as PT & IPT user.
- **Educational Qualification:** Respondents with higher educational qualifications have a high probability (71.7%) of getting classified as a multimodal traveller, and conversely, those with lesser educational qualifications have a high probability (81.7%) of getting classified as PT & IPT users.
- **Number of Years of Smartphone Use:** Experience with smartphone usage is a major contributor to app usage, and all users with less than three years of experience have been PT & IPT users. Although users with 3 to 5 years of experience with smartphone use also have a high probability (86.9%) of getting classified as PT & IPT users, there is also some probability (13.1%) of getting classified as a multimodal traveller. Users with more than five years of smartphone use experience have a 47.9% probability of getting classified as a multimodal user, 37.9% probability of getting classified as private vehicle users and still 14.2% probability of getting classified as PT & IPT users.
- **Household Composition:** Respondents with children below 18 have a slightly higher probability (36.3%) to be classified as a multimodal traveller, and those with children below 18 have a higher probability (46.6%) to be classified as PT & IPT users.
- **Monthly Household Income:** Respondents with a monthly income of less than INR 20,000 have been classified as PT & IPT users. Those earning INR 20,000 to 50,000 are highly likely (49.1%) to be classified as multimodal travellers. Among the high-income households, those belonging to ones with income INR 50,000 to 100,000 has a slightly higher probability of being classified as private vehicle user (50.9%) than multimodal traveller (49.1%). Interestingly though, there is a significantly high probability (70.8%) for respondents belonging to households earning more than INR 100,000 monthly to be classified as a multimodal traveller.

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- **Vehicle Ownership:** Respondents belonging to households with no four-wheeler or two-wheeler vehicle ownership have a very high probability (91.8% and 89.6%, respectively) to be classified as PT & IPT users. However, the ownership of even a single four-wheeler or two-wheeler ensures that they have a high probability (48.9% and 38.9%, respectively) of being classified as private vehicle users and a significant probability (47.6% and 36.1%, respectively) of being classified as a multimodal user. Respondents belonging to households with more than two vehicles have a very high probability of being classified as private vehicle users.

3.3.2.Attitudes and Preferences

Associations of respondent's attitudes and preferences with class membership have also been studied separately. Figure 6 shows latent class cluster-wise weighted mean exploratory factor analysis scores for statements relating to the choice of travel. Statement excluded from the LCCA is also included in the radar graphs for a more comprehensive overview of all studied aspects.

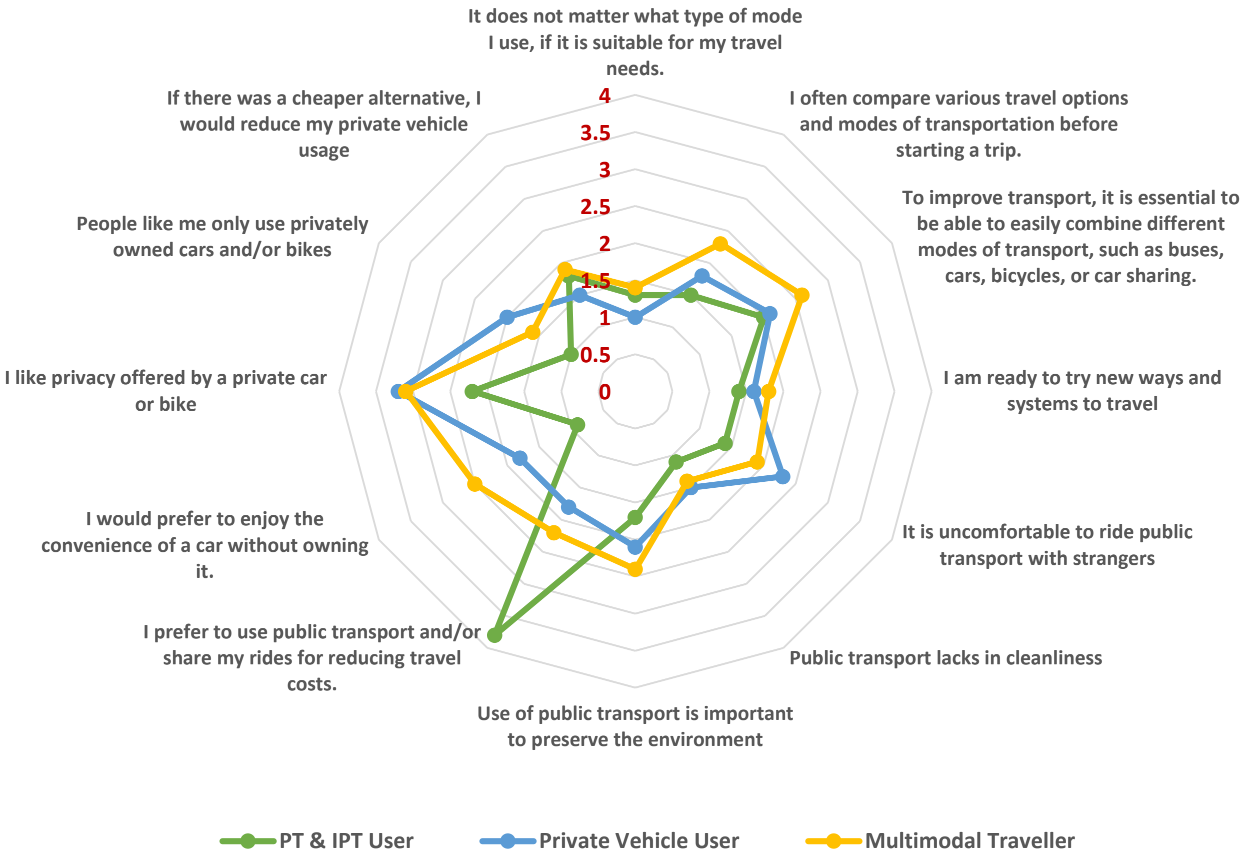

Figure 6. Weighted mean EFA scores for choice of travel

Respondents who compare travel options, choose the mode of transport per their travel needs and are willing to try new travel modes have a very high probability of being clustered as multimodal traveller who also highly rates multimodality. As per the responses, these users have a high probability of being pro-environment, feels a little uncomfortable riding with strangers and are most likely to reduce car dependence if a cheaper alternative is provided, preferably something that can provide the convenience of a car without owning one. They do give some consideration to reducing the trip costs by using public transport and shared mobility services. However, if a respondent is highly

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cost-sensitive, there is a high probability of being classified as a PT & IPT user who has the most stated disagreement with all the statements. The users were more inclined towards vehicle ownership, less comfortable with public transport and moderately willing to try new services, has a high probability of getting classified as private vehicle users.

4. Discussion

In this section, key findings of the study have been discussed and some policy recommendations for each cluster have also been provided.

- PT & IPT User cluster includes respondents who are primarily dependent on the usage of public transport and intermediate public transport. It comprises either younger or very old users with lower educational qualification and belonging to low-income households. They have less experience using smartphones and show less dependence on app usage for transport needs. These users are susceptible to the cost of travel which makes them captive to their choice of transport, and they are not willing to make different mobility choices unless they are technologically accessible to them and are cheaper than the existing system of their choice. Thus, their choices are not based on other concerns like comfort, cleanliness, privacy, or environmental friendliness. So, it becomes imperative for policymakers to ensure that the traditional forms of public transport and IPT are not compromised while introducing a smartphone-oriented mobility ecosystem, and the new systems must be integrated around the existing transit options as an additional choice for the users. Given incentives, coupled with increasing familiarity with smartphones and cost-saving alternatives, these users may even be willing to shift to the newer travel platforms.
- The *Multimodal Traveller* cluster includes respondents who choose to travel with various transport modes depending upon their requirements. It primarily comprises highly educated younger users belonging to medium and high-income households. They have extensive experience with the use of smartphones and show very high dependence on app usage for their transport needs. They often compare different travel options available to them, including the combination of modes for their trips and are even willing to try new mobility choices. Even though they are slightly uncomfortable with the prospect of riding with strangers and the cleanliness of public transport is a concern to them, they acknowledge that the use public transport is essential for preserving the environment and are very open to the idea of shared mobility where they can get the convenience of a private vehicle without the need to own them. For users in this group, the cost is also not a big issue, so they can become early adopters and significant users of the new smartphone-based mobility platform while reducing the private vehicle use for other modes. Also, given their attitudes towards traditional transport, we can expect them to (slightly) reduce the usage of public transport by shifting to app-based on-demand services. Focusing on practical benefits which services like MaaS offer, awareness campaigns can help this group shift away from private transport while also avoiding substantial departures from the usage of public transport based on the environmental sensitivity.
- The *Private Vehicle User* cluster includes respondents dependent on private modes of transport. It comprises medium- to old-age users primarily belonging to medium- and high-income households. They have moderate experience with using smartphones and show medium dependence on app usage depending on specific purposes. Although the users in this group somewhat acknowledge the importance of public transport for improving the environment, they are less inclined to try new mobility options compared to multimodal users due to their high degree of discomfort in riding with strangers. Instead, they are more inclined towards owning a vehicle and moderately willing to try new services compared to public transport. Although cost is not a problem for them, inducing a behavioural shift is very difficult with this group. Previous research suggests that new mobility options for these users

should be promoted as an alternative only in the absence of a private transport rather than a complete replacement of vehicles [33].

5. Conclusions

The transport sector is primarily fossil fuel driven and responsible for environmental externalities, including greenhouse gases. Policymakers are considering a wide range of measures, including technological developments and policy measures, low-carbon mobility, and technologies that play an essential role in this process, mainly through the application of ICT in the sector. Smartphone applications or "apps" represent such innovation and have helped create an ecosystem of smartphone-based mobility services. However, the market for smartphones and their applications is still developing, and it is unclear how they will affect everyday mobility patterns of users in the future with these continuous changes and improvements. Examining the relationship between smartphone app usage and frequency of use of transport systems can thus provide insight into the potential impact of smartphone app usage on people's mobility preferences.

In this context, latent class analysis has been used to probabilistically classify smartphone users into three traveller groups (or clusters) in the National Capital Territory of Delhi, each characterised by similar usage whilst maximising heterogeneity between groups. It has been observed that respondents categorised in cluster 1 show a very high reliance on public transport and intermediate public transport, very low reliance on private vehicles, and no use of taxis/app-based taxis. On the other hand, those classified in cluster 2 show a significant dependence on all modes of transport. Finally, cluster 3 respondents show a greater reliance on private vehicles. From the analysis of app usage patterns for trip planning activities and other travel-impacting purposes, it can be concluded that users with lower app dependency have high probability of getting classified in cluster 1 as PT and IPT users. Users with higher app dependency have high probability of getting classified in cluster 2 as multimodal travellers, and those with moderate app dependency are most likely to be classified in cluster 3 as private vehicle users.

In addition to depicting the three latent class clusters of travellers, an attempt has been made to analyse the mentioned covariates as factors which affect the probabilities of individuals to belong to these clusters, especially for the multimodal users with high app usage. It can be observed that male and female respondents are relatively less likely to be classified as multimodal travellers than PT & IPT users. Younger respondents are more likely to be classified as multimodal travellers and less likely to be classified as private vehicle users. In addition, respondents with higher education are highly likely to be classified as multimodal travellers. Smartphone usage experience is a major contributor to app usage, and users with more than five years of smartphone usage experience are very likely to be classified as multimodal users. Respondents who belong to households with children under 18 are slightly more likely to be classified as multimodal travellers. The respondents who earn INR 20,000 to INR 50,000 have a great chance of being classified as multimodal travellers. Among the families with a high income, those who belong to households with income between INR 50,000 and INR 100,000 have a slightly higher possibility of being classified as a user of private vehicles than the multimodal traveller. It is interesting, however, that there is a considerably high possibility that the respondents belonging to households who earn more than INR 100,000 monthly to be classified as multimodal travellers. The ownership of four-wheeled or two-wheeled vehicles ensures that they have a high possibility of being classified as a user of private vehicles and a strong possibility of being classified as a multimodal user too. Multimodal travellers compare travel options, choose the mode of transport per their travel needs and are willing to try new travel methods. As per the responses, these users are pro-environment, feel a little uncomfortable riding with strangers and are most likely to reduce car dependence if a cheaper alternative is provided, preferably something that can provide the convenience of a private transport modes like cars and bikes without owning one.

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The new app-based mobility concepts, such as MaaS, help make cities more flexible. Although environmental awareness is not a necessity for adoption of these services, it can be argued that these platforms can bring value to users by boosting reliability, lowering prices, and facilitating multimodal travel. They also have the potential to create more sustainable transport systems by making public transport more attractive and helping stimulate modal transfers. It can also facilitate more inclusivity by addressing the potential needs of neighbouring and adjacent areas that do not have sufficient access to public transport. All these can help in establishing low-carbon mobility.

For PT & IPT Users, policymakers should ensure that the new smartphone-enabled mobility platforms must be integrated around the existing transit options as an additional choice for the users. Given incentives, coupled with increasing familiarity with smartphones and cost-saving alternatives, these users may even be willing to shift to the newer travel platforms. The multimodal users can (slightly) reduce the usage of public transport by shifting to app-based on-demand services as early adopters, and travel awareness campaigns can help this group move away from private transport while avoiding substantial departures from the usage of public transport based on the environmental sensitivity. Inducing a behavioural shift is very difficult with private vehicle users, and research suggests that new mobility options for these users should be promoted as an alternative only in the absence of a private transport rather than a complete replacement of vehicles.

These innovative transportation platforms and policies are also important because they link into Goal 11 for Sustainable Development Goals - "*Make cities inclusive, safe, resilient and sustainable*", as decrease in air pollution from transport sector allows for a better quality of life along with sustainable growth of the urban centres and its residents. Also, in accordance with the Paris Agreement's objective of limiting the rise of average global temperature to well below 2 degrees Celsius from 2005 levels, the intended decrease in emission from transport sector as a result of implementing the app-based mobility platforms also contribute towards the Goal 13 of Sustainable Development Goals - "*Climate Action*", which encourages limiting the impacts of climate change by decreasing greenhouse gas emissions.

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