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Accounting for the Influence of Attitudes and Perceptions in Modeling the Adoption of Emerging Transportation Services and Technologies in India

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Abstract

Many rapidly developing countries around the world are at a crossroads when it comes to transportation, air quality, and sustainability. Indeed, the challenges presented by vehicular growth in India have motivated the search for sustainable transportation solutions. One solution constitutes ridehailing services, which are expected to reduce car ownership and provide affordable means of transportation. Another key solution is the rise of electric vehicles (EVs), which are expected to reduce greenhouse gas emission and address the growing demand for sustainable urban mobility. Using a unique survey data set collected in 2018 from a sample of 43,000 respondents spread across 20 cities in India, this paper attempts to shed light on the factors that affect adoption of on-demand transportation services and EVs in India. In particular, not only does this paper consider the socio-economic and demographic variables that affect these behavioral choices, but the modeling framework adopted in this study places a special emphasis on representing the important role played by attitudes, values, and perceptions in determining adoption of on-demand transportation services and EVs. It is observed that attitudes and values significantly affect the use of on-demand transportation services and EV ownership, suggesting that information campaigns and free trials/ demonstrations would help advance the adoption of sustainable transportation modes. The model results help in the identification of policy options and infrastructure investments that can advance a sustainable transportation future in India.

Keywords

on-demand transportation (Ola/Uber), electric vehicles, attitudes and perceptions, integrated choice and latent variable modeling

Developing countries around the world have experienced phenomenal growth in vehicle ownership and use over the past few decades. India is a rapidly developing economy with a population of about 1.4 billion people and is scheduled to take over as the most populous country in the world within the next few years (*1*). Rapid and consistent economic development over the past few decades has fueled the rise of the middle class that is increasingly urban, educated, and globalized and numbers anywhere between 100 and 600 million people depending on the criteria and thresholds used to define this segment of the population (*2, 3*). Although the middle class was adversely impacted during the COVID-19 pandemic, it is

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likely that any setback is only temporary and the purchasing power of the Indian middle class will continue to rise as the country emerges from the pandemic (*4*).

The growth of the middle class in India has been accompanied by a surge in vehicle ownership and use. According to data published by the Ministry of Road Transport and Highways (MoRTH) of the Government of India, the number of cars, jeeps, and taxis increased from 695,400 in 1971 to 33,649,000 in 2017 (*5*). The number of two-wheelers experienced a surge from just about 587,100 in 1971 to approximately 187 million in 2017. Both cars/jeeps/taxis and two-wheelers essentially experienced a compounded annual growth rate of more than 10% between 2007 and 2017 (*5*). Transportation contributes substantially to air pollution in India, accounting for 11% of all greenhouse gas (GHG) emissions, one-third of particulate matter pollution, and an even higher proportion of nitrogen oxides—all of which are harmful to human health (*6, 7*).

The air pollution, energy intensity, and infrastructure congestion challenges presented by transportation in India have motivated the search for sustainable transportation solutions that will reverse the growth in automobile use, carbon emissions, and fossil fuel consumption (*8*). According to recent articles by the International Council on Clean Transportation (ICCT), it is imperative that the nation embrace emerging vehicular technologies to reverse the growth in India's road transport emissions. The ICCT notes that battery EVs, for example, have the lowest lifecycle GHG emissions, both today and into the foreseeable future (*9*). Thus, transportation electrification is seen as a mechanism by which the negative externalities from growth in road transportation can be mitigated to a substantial degree. Indeed, there is growing adoption of electric vehicles (EVs) in the Indian market, achieving a growth rate of 44% with about one million units sold in the 2020 financial year (*10*).

Besides electrification, another potential mobility solution that may help soften the negative impacts of road transportation is the rise of ridesharing or ridehailing services. In India, two of the most popular ridehailing services are Uber and Ola. Both of these companies offer on-demand door-to-door mobility services via a smartphone app that can be used to summon a ride in real time, track vehicle location and trajectory, and make payment for a completed ride. Ridehailing services have experienced impressive growth in India. Unconfirmed numbers suggest that Uber served 14 million rides per week in 2019, while Ola recorded more than 28 million bookings per week during 2018–2019 (including all types of mobility-on-demand services) (*11*). While these services often provide private rides to individuals, they offer the potential for advanced shared mobility services where multiple individuals share a ride (similar to a carpool). Ridesharing is being identified as one among the strategies that a country such as India should embrace to help mitigate the adverse effects of private automobile use (*12*). If the fleets transition to EVs in the future, the cause of sustainable transportation may be advanced further.

This study aims to identify the factors contributing to the adoption of these two promising transportation innovations in the Indian context. Using survey data collected from more than 43,000 respondents from across the nation, the study simultaneously models the use of ridehailing services and the ownership of an EV. Although these two endogenous variables do not directly affect one another, the modeling framework accommodates an error correlation across these two endogenous variables to account for the possible presence of correlated unobserved attributes that simultaneously influence adoption of ridehailing services and ownership of an EV. What is particularly unique about this study is that it incorporates the influence of latent attitudinal constructs in a holistic model structure, thus enabling the identification of the role of attitudes, perceptions, and preferences in determining the adoption of on-demand mobility services and EV ownership. The latent attitudinal constructs are themselves treated as endogenous variables with socioeconomic and demographic variables serving as exogenous variables. The entire model system is estimated in one step using an enhanced integrated choice and latent variable modeling approach that provides the ability to unravel complex relationships among multiple behavioral phenomena of interest.

There are several past studies that have focused on modeling the adoption and use of ridehailing services (e.g., Malik et al. [*13*], Wadud [*14*], Lavieri and Bhat [*15*], Alemi et al. [*16*]) and the adoption and ownership of EVs (e.g., Dua et al. [*17*], Shalender and Sharma [*18*], Langbroek et al. [*19*]). Ridehailing services are generally used to a greater degree by individuals who are younger, more highly educated, employed, and residing in urban contexts (*13, 16*). EVs are generally found to be adopted and owned by individuals who are older, have higher income, and reside in urban areas where charging infrastructure may be better and distances between trip origins and destinations are likely to be shorter than in more suburban and rural settings (*18, 20*). While EVs constitute a transportation innovation with clear positive benefits from a GHG emission reduction perspective, the potential for on-demand mobility services to bring about GHG emission reductions remains uncertain. On the one hand, on-demand mobility services may elevate automobile use at the expense of alternative mode use, thus resulting in a detrimental impact on air quality. On the other hand, if used in a shared modality, on-demand mobility services may contribute to a substantial reduction in private car use, thus leading to positive impacts

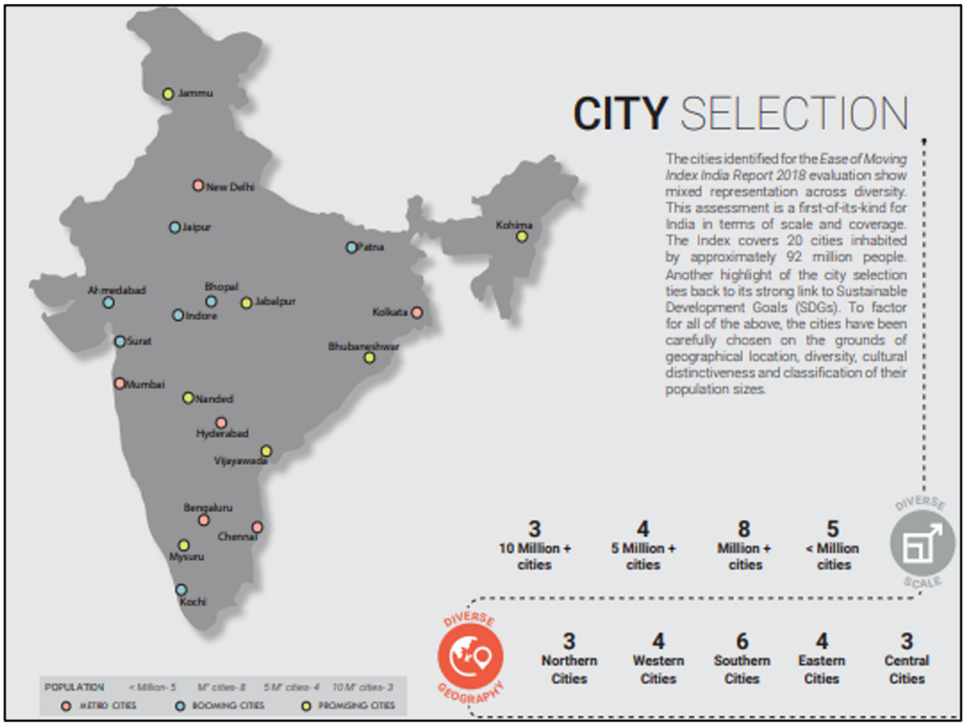

Figure 1. Map showing data collection sites in India.
Source: Ola Mobility Institute (*22*).

on congestion and pollution (*21*). Despite the rich body of literature dedicated to ridehailing usage and EV adoption, there is very little research that explicitly explores the interaction between these transportation innovations—particularly in developing countries such as India. This study therefore fills an important gap in the literature and sheds new light on the adoption of promising new transportation technologies in the Indian context, while explicitly accounting for attitudinal variables within a holistic integrated modeling framework.

The remainder of this paper is organized as follows. The next section provides a detailed description of the survey and data set used in this study, together with descriptive statistics about the endogenous variables of interest. The third section presents the model structure and the modeling methodology. The fourth section presents model estimation results. A discussion of the implications of the findings and conclusions is furnished in the fifth and final section.

Description of Survey and Data Set

The data for this study is derived from a comprehensive survey effort undertaken in India by the Ola Mobility Institute as part of its Ease of Moving Index framework. In 2018, a detailed survey capturing socio-economic, demographic, mobility, and attitude/perception variables was conducted across 20 cities in India (with a collective population of 90 million) as shown in Figure 1. The cities were of various sizes and were categorized as promising cities (identified with yellow dot), booming cities (identified with blue dot), and metro cities (identified with pink dot). The cities spanned the entire country, and a total of more than 43,000 survey responses were obtained. Each survey respondent answered nearly 50 questions, thus providing a wealth of data for understanding people's preferences, mobility choices, and perceptions of mobility services, public transport, and state of roadways. The survey included questions that addressed issues of sustainability and public transport usage. Barriers related to advancing more sustainable modes of transport or public transport usage were identified through the survey. Complete details about the survey may be found elsewhere (*22*). The survey was administered in person by survey personnel who visited households randomly to administer the survey.

This section presents the characteristics of the survey sample extracted for use in this study. Sample characteristics are presented in the first subsection and a more in-depth examination of endogenous variables and attitudinal indicators of interest is presented in the second subsection.

Sample Characteristics

In general, the estimation of a joint econometric model that incorporates multiple latent constructs on a sample size of 43,000 is rather computationally prohibitive. For purposes of computational tractability, a random sample of 7,500 respondents was extracted from the large sample. The characteristics of the 7,500 individuals were compared in detail against the original 43,000 + sample to ensure that the extracted subsample was not systematically different in any way. Once the representativeness of the extracted subsample was established, further filtering was done. First, only those individuals who reside in households with at least one vehicle were included in the analysis subsample. Second, any records with missing data on critical socio-economic, attitudinal, or endogenous behavioral variables of interest were excluded. The final analysis subsample consists of 2,972 persons, all of whom reside in a household with at least one vehicle. The analysis had to be limited to such households because one of the key endogenous variables of interest is EV ownership. As households with zero vehicles would have no opportunity to own any vehicle (let alone an EV), it was considered prudent to limit the analysis to households that own at least one vehicle.

Table 1 presents the socio-economic and demographic characteristics for this subsample of 2,972 respondents. The sample is predominantly female, comprising 65.3% of the sample. About 59% of the sample is 20–40 years and 22% is 40–60 years of age. About 63% report being employed, about 12.6% report being a homemaker, and 15.1% indicate that they are students. The monthly income is reported for employed individuals. It is found that 27.8% of all individuals (not just employed individuals) report a monthly income between ₹30,000 and ₹50,000 (Indian Rupees) and another 12.1% report income between ₹50,000 and ₹100,000. The educational attainment variable shows that nearly 40% have a college degree, and another 31% have attained a post-graduate degree. About 11% have a doctoral degree, suggesting that this subsample is more highly educated relative to the general population in India.

For vehicle ownership, a distinction is made between two-wheelers and four-wheelers (cars). About 22% of individuals report owning no two-wheelers, 54% report owning one two-wheeler, and 20.7% report owning two two-wheelers. With respect to cars, there are no zero-car individuals because of the nature of the subsample. About 73% own one car and 25% own two cars. The travel time to work distribution shows that 27.5% have a one-way commute time of 15–30 min. If one were to consider the number of kilometers traversed for daily commuting, it is seen that 38.3% commute 20–40 km and 27.7% commute 40–60 km. Monthly expenditures for transport show that 24.2% spend more than ₹5,000 for transport; only 5.1% spend less than ₹1,000. Public transport is a preferred mode of transportation for only 17.8% of the subsample of respondents; this percentage is lower than for the sample overall, largely because of the car-owning nature of the subsample. Overall, the sample offers the richness of variation in various characteristics that would render it suitable for use in econometric choice modeling efforts.

Endogenous Variables and Attitudinal Indicators

This study is concerned with the adoption of new and emerging transportation technologies in India. As such, two endogenous variables are of interest. The first is the adoption and use of *on-demand transportation or ridehailing services* (e.g., Uber, Ola). The second endogenous variable corresponds to *EV ownership* (vehicle fuel type choice). The distributions for these two endogenous variables are shown at the end of Table 1. With respect to on-demand transportation services, 91% of the respondents indicate that they never use such services. About 8% use the services frequently (daily/weekly) and a modest 1% use the services rarely. In relation to fuel type, each individual was asked to report on the vehicle that he or she drives and uses: 7% of respondents indicated that they own and use an EV. Given the income and education profile of the respondent subsample, it is not too surprising to see the higher rate of EV penetration in the subsample relative to the general population. In the modeling exercise of this paper, no explicit relationship is assumed between EV ownership and on-demand transportation mode use. However, an error correlation is incorporated to reflect the possible presence of correlated unobserved attributes affecting both outcomes.

In addition to the two behavioral outcomes of interest, the model system incorporates two latent attitudinal constructs. The first construct represents *car owning proclivity*. Figure 2 shows the distribution of respondents with respect to the attitudinal indicators that define this latent attitudinal construct. About 91% of this subsample consider owning a car important or very important. Car ownership is the second indicator defining this latent construct. The second latent construct captures the *environmentally friendly lifestyle*. Two indicators capture this latent construct as shown in the figure. It is interesting to note that, even though 91% of respondents consider it important or very important to own a car, it is also seen that 95% consider it important or very important for their means of transportation to be environmentally friendly. About 52% of respondents indicated that they believe that EVs will replace conventional vehicles by 2030 and only 29% indicated that they did not agree with the statement. These two indicators define the environmentally friendly lifestyle. The model framework adopted in this paper is described in the next section.

Table 1. Socio-Demographic and Travel Characteristics ($N = 2,972$ persons)

Socio-demographic and travel characteristics			
Exogenous variable: socio-demographic characteristics	Value (%)	Exogenous variable: travel characteristics	Value (%)
Gender		Travel time from home to work	
Female	65.3	<15 min	10.4
Male	34.7	15–30 min	27.5
Age category		30–60 min	19.8
<20 years	11.4	⩾60 min	5.6
20–40 years	59.3	Unemployed	36.7
40–60 years	22.1	Kilometers commuted in city daily on average	
⩾60 years	7.2	<10 km	5.4
Employment status		10–20 km	21.6
Employed	63.3	20–40 km	38.3
Homemaker/housewife	12.6	40–60 km	27.7
Student/studying	15.1	⩾60 km	7.0
Unemployed	9.0		
Monthly income for employed individuals (per month in Indian rupees)		%age of monthly salary spent on transport (in Indian rupees)	
<₹15,000	2.0	<₹1,000	5.1
₹15,000–₹30,000	18.8	₹1,000–₹3,000	31.3
₹30,000–₹50,000	27.8	₹3,000–₹5,000	39.4
₹50,000–₹100,000	12.1	⩾₹5,000	24.2
⩾₹100,000	2.6	Preferred mode of transport	
Unemployed	36.7	Auto	20.6
Educational attainment		Non-motorized	4.6
High school	18.2	Personal vehicles	27.7
Graduate degree	39.7	Public transport	17.8
Post-graduate degree	30.9	Taxi/Cabs	29.3
Doctoral and above	11.2	**Endogenous variables**	
Number of two-wheelers owned		**On-demand transportation (Ola/Uber)**	
Zero vehicle	21.9	Never	90.9
One vehicle	53.9	Used rarely (monthly/yearly)	1.0
Two vehicle	20.7	Used frequently (daily/weekly)	8.1
Three or more vehicle	3.5	**Personal vehicle, fuel type use**	
Number of cars owned		Compressed natural gas (CNG)	11.4
One car	73.0	Diesel	35.3
Two cars	24.8	Electric	7.0
Three or more cars	2.2	Petrol	46.3

Modeling Framework

This section presents the model structure and the model estimation methodology employed in this paper. The methodology accommodates multiple endogenous variables (that do not affect one another directly), multiple latent attitudinal factors that affect the endogenous variables and are themselves affected by socio-economic variables, and flexible error correlation structures accounting for the presence of correlated unobserved attributes that simultaneously affect multiple endogenous variables.

Model Structure

The model structure adopted in this study is shown in Figure 3. A host of socio-economic, demographic, and travel related attributes serve as exogenous variables. There are two latent stochastic constructs, namely, *environmentally friendly lifestyle* and *car owning proclivity*, with a possible error correlation between them. Both of these latent attitudinal constructs are influenced by exogenous variables, and in turn, influence the endogenous variables. The two endogenous variables include EV ownership (binary dependent variable: yes or no) and on-demand transportation user (binary dependent variable: never used or used rarely/frequently). Some consolidation of categories had to be done to define the endogenous variables in the model structure because of very small sample sizes in certain end categories. Thus, this model structure is a bivariate model with two binary dependent variables that do not affect one another directly. However, an error correlation between the endogenous variables accounts for the presence of correlated unobserved attributes that simultaneously affect

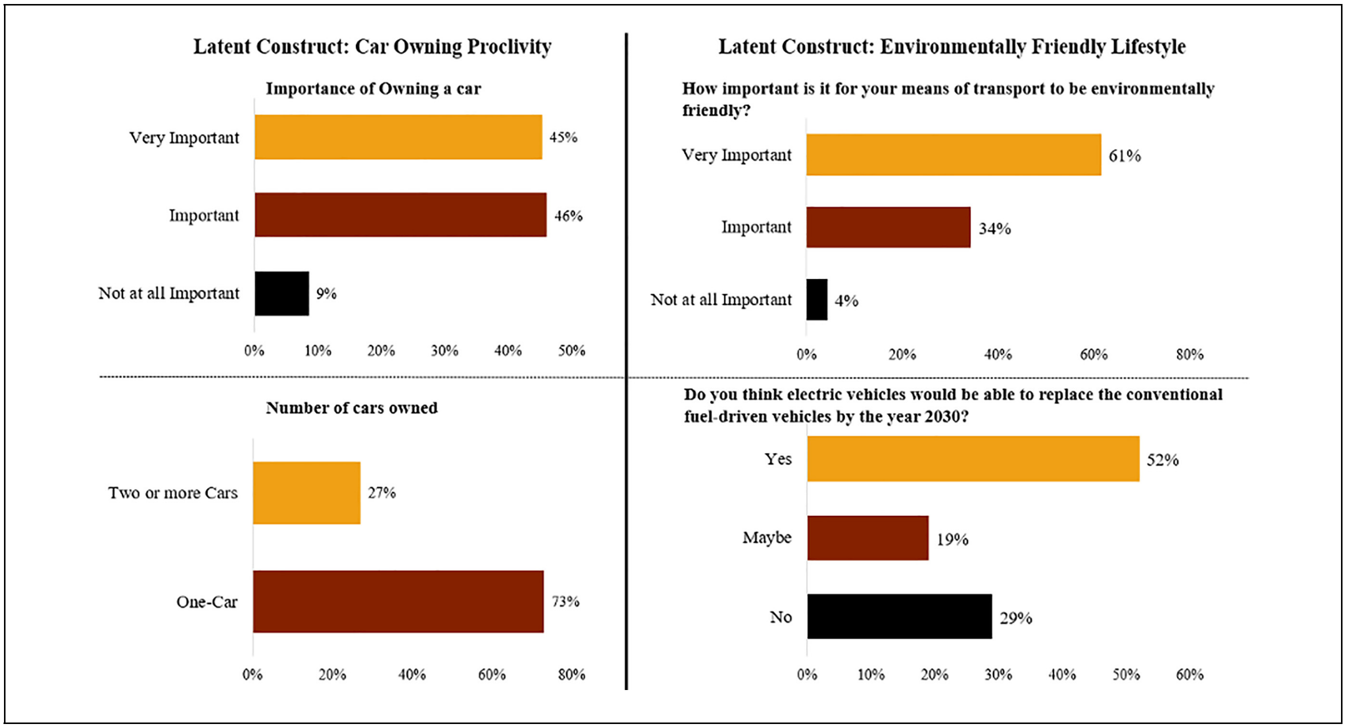

Figure 2. Indicator variables defining two latent attitudinal constructs.

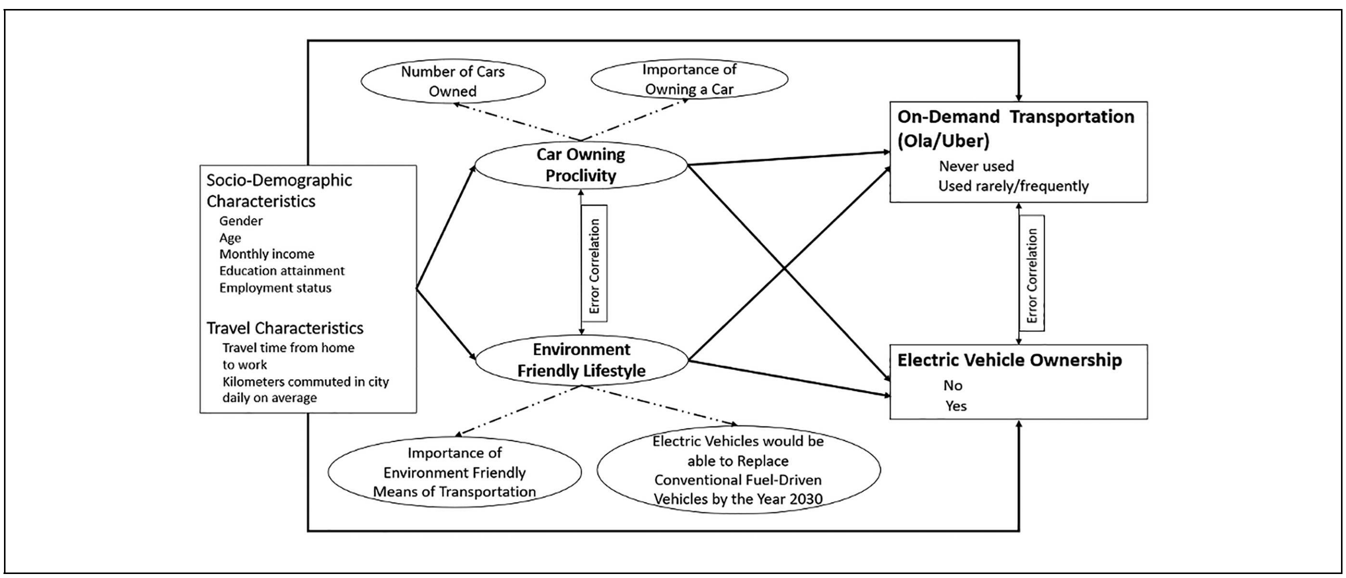

Figure 3. Structure of integrated choice and latent variable model system.

the two endogenous variables of interest. The latent attitudinal constructs affect the endogenous variables. Through the modeling framework presented in Figure 3, it is possible to capture the influence of both socio-economic and attitudinal variables on the adoption of emerging transportation services and technologies. The entire model structure is estimated in a single step using a novel methodology capable of reflecting endogeneity and multiple error correlations. The methodology is presented in the next subsection.

Model Estimation Methodology

In this section, the integrated choice and latent variable model, which has been proposed and applied for an unordered choice variable in the literature (e.g., Bhat and Dubey [23]), is modified to accommodate multiple correlated binary choices as needed for this study.

The model formulation begins by assuming that there are I correlated ordered choice variables c_i ($i = 1, 2, \ldots, I$) and their latent utility functions u_i^* are formulated as:

$$u_i^* = x_i\beta_i + z^*\gamma_i + {}_i. \tag{1}$$

In the above equation, x_i is a row vector of observed explanatory variables and z^* is a row vector of latent psychological factors while β_i and γ_i are two column vectors of coefficients in the respective utility function. $_i$ is a random component in each utility function and assumed to follow a standard multivariate normal distribution associated with a symmetric correlation matrix as:

$$cr = \begin{bmatrix} 1 & cr_{12} & \ldots & cr_{1I} \\ cr_{12} & 1 & \ldots & \ldots \\ \ldots & \ldots & 1 & cr_{I-1,I} \\ cr_{1I} & \ldots & cr_{I-1,I} & 1 \end{bmatrix}. \tag{2}$$

The utility function value of u_i^* will determine an ordered choice variable, denoted as c_i, based on comparisons against several ordinal thresholds, denoted as $\psi_{i,0}, \psi_{i,1}, \ldots \psi_{i,M_i}$ ($\psi_{i,0} < \psi_{i,1} \ldots < \psi_{i,M_i}$). Among those $(M_i + 1)$ thresholds, $\psi_{i,0} = -\infty$ and $\psi_{i,M_i} = +\infty$. When $\psi_{i,m-1} < u_i^* < \psi_{i,m}$, the ordered choice variable c_i takes the value M from the choice set $\{1,2,\ldots, M_i\}$. Note that a binary choice can be considered as a special case of ordered choices, where M_i takes the value of 2 and the choice set is $\{1, 2\}$.

In Equation 1, the row vector of latent psychological factors z^* contains J elements, each of which can be denoted as z_j^* ($j = 1, 2, \ldots, J$) and formulated as:

$$z_j^* = w_j\alpha_j + \eta_j. \tag{3}$$

In the above formula, w_j is a row vector of observed variables to explain z_j^* and α_j is a column vector of coefficients. η_j is a random component in the model and assumed to follow a standard multivariate normal distribution associated with a symmetric correlation matrix as:

$$zr = \begin{bmatrix} 1 & zr_{12} & \ldots & zr_{1J} \\ zr_{12} & 1 & \ldots & \ldots \\ \ldots & \ldots & 1 & zr_{J-1,J} \\ zr_{1J} & \ldots & zr_{J-1,J} & 1 \end{bmatrix}. \tag{4}$$

Each latent psychological factor z_j^* can influence one or more latent propensity function values, which in turn determine the same number of observed ordinal indicators (e.g., the extent to which one agrees on a certain statement). In total, there are K such latent propensity function values, which are denoted as $y_1^*, y_2^*, \ldots, y_K^*$ and laterally combined to form a row vector y^*. The relation between z^* and y^* can be expressed as:

$$y^* = z^* \cdot \mathrm{z2y} \cdot d + \xi. \tag{5}$$

In the above formula, $z2y$ is a dummy matrix of J rows and K columns, indicating whether a factor in z^* influences a latent propensity value in y^*. When an element in jth row and kth column of the matrix takes the value of 1, the jth factor in z^* does influence the kth propensity value in y^*. When it takes the value of 0, there is no influence. For example, $z2y = \begin{bmatrix} 1 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix}$, indicating that there are two psychological factors and three ordinal indicators, where the first factor influences the first and second propensity values and the second factor influences the third value. Then, d is a column vector of K loading factors while ξ is a row vector of random components following independent standard normal distribution.

The propensity function values of y_k^* will determine an observed ordinal indicator, denoted as y_k, based on comparisons against several ordinal thresholds, denoted as $\theta_{k,0}, \theta_{k,1}, \ldots \theta_{k,N_k}$ ($\theta_{k,0} < \theta_{k,1} \ldots < \theta_{k,N_k}$). Among those $(N_k + 1)$ thresholds, $\theta_{k,0} = -\infty$ and $\theta_{k,N_k} = +\infty$. When $\theta_{k,n-1} < \mathrm{y}_i^* < \theta_{k,n}$, the ordinal indicator takes the value N from the set $\{1,2,\ldots, N_k\}$.

To estimate the model, the latent variables in Equation 3 can be substituted into Equations 1 and 5 to obtain new equations as shown below:

$$u_i^* = x_i\beta_i + \sum\nolimits_{j=1}^{J}\left(w_j\boldsymbol{\alpha_j} + \eta_j\right)\gamma_{ij} + \varepsilon_i = x_i\beta_i + \sum\nolimits_{j=1}^{J}\left(w_j\boldsymbol{\alpha_j}\gamma_{ij}\right) + \sum\nolimits_{j=1}^{J}\left(\eta_j\gamma_{ij}\right) + \varepsilon_i = V_i + \sum\nolimits_{j=1}^{J}\left(\eta_j\gamma_{ij}\right) + \varepsilon_i, \tag{6}$$

$$\begin{aligned} y_k^* &= \sum\nolimits_{j=1}^{J}\left(w_j\boldsymbol{\alpha_j} + \eta_j\right)\cdot z2y_{jk}\cdot d_k + \xi_k \\ &= \sum\nolimits_{j=1}^{J}\left(w_j\cdot\boldsymbol{\alpha_j}\cdot z2y_{jk}\cdot d_k\right) + \sum\nolimits_{j=1}^{J}\left(\eta_j\cdot z2y_{jk}\cdot d_k\right) + \xi_k \\ &= T_k + \sum\nolimits_{j=1}^{J}\left(\eta_j\cdot z2y_{jk}\cdot d_k\right) + \xi_k. \end{aligned} \tag{7}$$

Thus, the variance-covariance matrix $COV\left(u_i^*\right) = \Lambda'\cdot zr\cdot\Lambda + cr = COV1$, where $\Lambda = [\gamma_1, \gamma_2, \ldots, \gamma_I]$, a matrix formed by laterally combining the column vectors γ_i. The variance-covariance matrix $COV\left(u_i^*, y_k^*\right) = \Lambda'\cdot zr\cdot z2y * d' = COV2$, where "." represents matrix multiplication and "*" represents element-wise multiplication. The variance-covariance matrix $COV(y_k^*) = (\mathrm{d} * \mathrm{z2y}')\cdot zr\cdot(\mathrm{z2y} * \mathrm{d}') = COV3$. By comparing latent variables (i.e., u_i^* or y_k^*) against corresponding thresholds, ordered choices or ordinal indicator values can be determined while random components in latent variables follow a multivariate normal distribution associated with covariance matrices $COV1$, $COV2$, and $COV3$. Thus, a multivariate ordered probit model can be formulated and a composite maximum likelihood estimation method can be employed for model estimation. The composite likelihood function consists of three parts that incorporate all of the coefficients to be estimated.

The first part is formulated to incorporate coefficients in $COV1$ as:

$$LL_1(\cdot) = \sum_{i=1}^{I-1} \sum_{j=i+1}^{I} \sum_{m=1}^{M_i} \sum_{n=1}^{M_j} \{I(c_i = m) \cdot I(c_j = n) \cdot \ln[P(c_i = m, c_j = n)]\}. \quad (8)$$

In the above formula, $P(c_i = m, c_j = n)$ represents the joint choice probability from a bivariate ordered probit model and can be expressed as:

$$\begin{aligned} &\Phi_2\left[\delta_i(\psi_{i,m} - V_i), \delta_j(\psi_{j,n} - V_j), \delta_i\delta_j\rho_{ij}\right] - \\ &\Phi_2\left[\delta_i(\psi_{i,m-1} - V_i), \delta_j(\psi_{j,n} - V_j), \delta_i\delta_j\rho_{ij}\right] - \\ &\Phi_2\left[\delta_i(\psi_{i,m} - V_i), \delta_j(\psi_{j,n-1} - V_j), \delta_i\delta_j\rho_{ij}\right] + \\ &\Phi_2\left[\delta_i(\psi_{i,m-1} - V_i), \delta_j(\psi_{j,n-1} - V_j), \delta_i\delta_j\rho_{ij}\right], \end{aligned} \quad (9)$$

where $\delta_i = \frac{1}{\sqrt{COV1_{ii}}}$, $\delta_j = \frac{1}{\sqrt{COV1_{jj}}}$, $\rho_{ij} = COV1_{ij}$ and $\Phi_2[x, y, \rho]$ is the cumulative distribution function of the standard bivariate normal distribution.

The second part is formulated to incorporate coefficients in $COV2$ as:

$$LL_2(\cdot) = \sum_{i=1}^{I} \sum_{k=1}^{K} \sum_{m=1}^{M_i} \sum_{n=1}^{N_k} \{I(c_i = m) \cdot I(y_k = n) \cdot \ln[P(c_i = m, y_k = n)]\}. \quad (10)$$

In the above formula, $P(c_i = m, y_k = n)$ can be expressed as:

$$\begin{aligned} &\Phi_2\left[\delta_i(\psi_{i,m} - V_i), \delta_k(\theta_{k,n} - T_k), \delta_i\delta_k\rho_{ik}\right] - \\ &\Phi_2\left[\delta_i(\psi_{i,m-1} - V_i), \delta_k(\theta_{k,n} - T_k), \delta_i\delta_k\rho_{ik}\right] - \\ &\Phi_2\left[\delta_i(\psi_{i,m} - V_i), \delta_k(\theta_{k,n-1} - T_k), \delta_i\delta_k\rho_{ik}\right] + \\ &\Phi_2\left[\delta_i(\psi_{i,m-1} - V_i), \delta_k(\theta_{k,n-1} - T_k), \delta_i\delta_k\rho_{ik}\right] \end{aligned} \quad (11)$$

where $\delta_i = \frac{1}{\sqrt{COV2_{ii}}}$, $\delta_k = \frac{1}{\sqrt{COV2_{kk}}}$, $\rho_{ik} = COV2_{ik}$.

The third part is formulated to incorporate coefficients in $COV3$ as:

$$LL_3(\cdot) = \sum_{k=1}^{K-1} \sum_{j=k+1}^{K} \sum_{m=1}^{N_k} \sum_{n=1}^{N_j} \{I(y_k = m) \cdot I(y_j = n) \cdot \ln[P(y_k = m, y_j = n)]\}. \quad (12)$$

In the above formula, $P(y_k = m, y_j = n)$ can be expressed as:

$$\begin{aligned} &\Phi_2\left[\delta_k(\theta_{k,m} - T_k), \delta_j(\theta_{j,n} - T_j), \delta_k\delta_j\rho_{kj}\right] - \\ &\Phi_2\left[\delta_k(\theta_{i,m-1} - T_k), \delta_j(\theta_{j,n} - T_j), \delta_k\delta_j\rho_{kj}\right] - \\ &\Phi_2\left[\delta_k(\theta_{i,m} - T_k), \delta_j(\theta_{j,n-1} - T_j), \delta_k\delta_j\rho_{kj}\right] + \\ &\Phi_2\left[\delta_k(\theta_{i,m-1} - T_k), \delta_j(\theta_{j,n-1} - T_j), \delta_k\delta_j\rho_{kj}\right], \end{aligned} \quad (13)$$

where $\delta_k = \frac{1}{\sqrt{COV3_{kk}}}$, $\delta_j = \frac{1}{\sqrt{COV3_{jj}}}$, $\rho_{kj} = COV3_{kj}$. When there are many ordinal indicators and K takes a large integer value, it is unnecessary to incorporate all K ordinal indicators into Equation 12. Instead, a subset of representative indicators can be selected for each latent factor in z^* to form a new subset of ordinal indicators to compute $LL_3(\cdot)$ and thereby achieve computational efficiency. Finally, all three parts can be added to form a composite log-likelihood function with respect to all of the model coefficients as:

$$LL(\alpha, \beta, \gamma, d, \psi, \theta, zr, cr) = LL_1(\cdot) + LL_2(\cdot) + LL_3(\cdot). \quad (14)$$

The composite log-likelihood function above and its analytical gradient are coded in Gauss matrix programming platform (*24*), where the composite log-likelihood function can be maximized to consistently estimate all coefficients and a sandwich robust covariance matrix can be computed for statistical inferences on parameter estimates.

Model Estimation Results

Detailed model estimation results are presented in this section. The entire model system is estimated as a joint model through a methodological framework that enables parameter estimation in a single step while fully accounting for the endogeneity of latent attitudinal constructs. Extensive exploratory data analysis was conducted to assess the distributions of, and correlations among, different variables in the data set. Model specification and structure was informed by the results of the exploratory data analysis and the final model specifications were determined based on behavioral intuitiveness, statistical significance and goodness-of-fit measures, and interpretability of model parameters. Estimation results are discussed separately for the latent construct model components and the dependent variable model components for ease of exposition.

Latent Construct Model Components

The latent construct model component estimation results are presented in Table 2. Two latent attitudinal constructs, *car owning proclivity* and *environmentally friendly*

Table 2. Determinants of Latent Variables and Loadings on Indicators

	Car owning proclivity		Environmentally friendly lifestyle	
	Estimate	*t*-Stat	Estimate	*t*-Stat
Exogenous variables				
Age				
<20 years	—	—	−0.846	−3.624
⩾ 60 years	0.189	1.441	—	—
Employment status				
Unemployed	−0.355	−2.650	−0.544	−2.823
Monthly income (Indian rupees)				
<₹15,000	—	—	−0.611	−2.205
Travel time from home to work				
<15 min	−0.831	−6.395	0.438	2.725
⩾ 60 min	0.490	3.320	−0.249	−2.072
Indicator variables: factor loadings				
Number of cars owned	0.685	4.841	NA	NA
Importance of owning a car	0.214	1.861	NA	NA
Importance of environmentally friendly means of transportation	NA	NA	0.483	2.643
Electric vehicles would be able to replace the conventional fuel-driven vehicles by the year 2030	NA	NA	0.643	2.817
Thresholds for indicator variables (in order as listed above)				
Threshold 1-1	0.701	13.08	NA	NA
Threshold 2-1	−1.406	−32.35	NA	NA
Threshold 2-2	0.139	5.314	NA	NA
Threshold 3-1	NA	NA	−1.986	−12.92
Threshold 3-2	NA	NA	−0.384	−8.732
Threshold 4-1	NA	NA	−0.749	−8.755
Threshold 4-2	NA	NA	−0.137	−3.956
Error correlation				
Car owning proclivity	NA	NA	−0.391	−2.530

Note: NA = not applicable.
"—" indicates that the variable is insignificant in the model.

lifestyle, are considered in this study. Factor loadings presented in Table 2 show that the indicators are appropriate and statistically significant in representing the latent attitudinal constructs. The number of cars owned and the level of importance attached to owning a car are both exhibiting positive factor loadings for the latent factor representing car owning proclivity. Similarly, the importance of an environmentally friendly lifestyle and the belief that EVs will replace conventional vehicles by 2030 load positively onto the latent factor representing an environmentally friendly lifestyle. As expected, the latent factors are negatively correlated with one another as they represent and capture opposite dimensions.

A range of socio-economic and demographic characteristics affect these latent factors. Younger individuals are found to be less environmentally oriented, a finding that is somewhat counter to expectations as some literature has shown that younger individuals tend to be more environmentally conscious (*25*). But some recent studies (see Lavieri and Bhat [*15*], Gifford and Nilsson [*26*]) also identify a decrease in the younger generation's environmental consciousness, suggesting that this may be the result of an increase in the importance of material pleasures among the young, as well as an increased level of optimism that technology will solve environmental problems. Also, there is recent evidence that suggests environmental consciousness is less about age, and more about level of awareness, information, and knowledge (*27*). Older individuals are more auto-oriented and show a greater level of car owning proclivity; this is consistent with expectations and previous findings in the literature (*28*). Those who are unemployed exhibit lower levels of car owning proclivity as well as less environmentally friendly lifestyles; once again, this finding is consistent with prior research and reflects that unemployed individuals do not have the income and information to lean positively toward either of these latent factors. Indeed, it is found that those with a lower income exhibit a lower level of environmental friendliness.

Commute time has a significant influence on the latent factors. Those with short commutes to work may not feel a compelling need for an automobile and therefore exhibit a lower level of car owning proclivity. They also exhibit a higher level of environmental friendliness.

Table 3. Joint Model of On-Demand Transportation Use and Electric Vehicle Ownership

	On-demand transportation (never used/used)		Electric vehicle ownership (no/yes)	
	Estimate	*t*-Stat	Estimate	*t*-Stat
Latent constructs				
Car owning proclivity	−0.335	−3.063	—	—
Environmentally friendly lifestyle	1.835	2.065	0.994	1.842
Exogenous variables				
Gender				
Female	0.100	1.536	−0.901	2.387
Age				
⩾ 40 years	—	—	−1.022	−2.288
Employment status				
Employed	−0.261	−3.106	−1.025	−2.340
Monthly income (Indian rupees)				
< ₹15,000	0.352	1.544	—	—
⩾ ₹50,000	−0.499	−3.089	—	—
⩾ ₹100,000	—	—	0.247	1.505
Education attainment				
Post-graduate and above	−0.252	−3.151	—	—
Average daily commute (kilometers)				
⩾ 40 km	−0.268	−3.163	−0.297	−1.431
Thresholds				
Threshold 1-1	1.153	13.29	NA	NA
Threshold 2-1	NA	NA	1.556	2.917
Error correlations				
On-demand transportation use	NA	NA	−0.042	−1.477
Model statistics:				
Number of observations = 2,972 individuals				
Number of parameters = 39				
Null log-likelihood (only thresholds) = −55,449				
Full log-likelihood (joint model) = −46,630				
Pseudo Rho-squared = 0.159				

Note: NA = not applicable.
"—" indicates that the variable is insignificant in the model.

On the other hand, those with long commutes exhibit a greater proclivity for car ownership and lower levels of environmental friendliness. These findings are consistent with results reported in the literature (*29*), where a close association between commute length and latent attitudinal factors toward car ownership and the environment have been reported (although the direction of causality remains open to debate).

Bivariate Model of Behavioral Outcomes

The bivariate model of on-demand transportation mode use and EV ownership is presented in Table 3. It should be noted that there is no direct effect between these two endogenous variables. In this particular model structure, there is no compelling reason or basis to assume that one endogenous variable directly affects the other. Therefore, rather than introduce a direct effect between the endogenous variables, the joint model specification and estimation procedure enables the computation of an error correlation between the endogenous variables to account for correlated unobserved attributes that may affect both behavioral dimensions of interest. In this instance, the error correlation is quite small, negative, and very weakly significant from a statistical standpoint. A variety of explanations are possible. For example, those who eschew mode sharing in favor of a lifestyle that emphasizes ownership are less likely to embrace on-demand transportation services. Note that neither of the latent constructs captures the proclivity toward *sharing* modes or vehicles; therefore the effect of this proclivity is likely being captured in the error correlation. This unobserved attribute has an opposite effect on the two endogenous variables, thus engendering a negative correlation.

The latent constructs are found to affect both endogenous variables and are statistically significant. Car owning proclivity decreases the probability of using on-demand transportation, as expected. On the other hand, an environmentally friendly lifestyle increases the probability of embracing and using on-demand transportation services and owning an EV. Thus, bringing about greater environmental awareness and providing incentives for individuals to embrace an environmentally friendly lifestyle will help elevate the uptake of both on-demand (possibly shared) transportation services and EVs.

The exogenous variables influence the endogenous variables along expected lines. Females are slightly more likely to use on-demand transportation services (consistent with recent research, e.g., Alemi et al. [*16*], International Finance Corporation [*30*]), although the coefficient is not statistically significant. In many developing countries, on-demand transportation services have provided mobility independence for females (who generally exhibit a much lower rate of driver's license holding than males) (*30*). Females are less likely to own EVs; this finding is consistent with the literature (e.g., Priessner et al. [*31*]) and is attributed to greater levels of range anxiety. Older individuals (more than 40 years of age), who are likely to have owned and used conventional vehicles for some time, are less likely to own EVs. Employed individuals, who are likely to have the monetary resources and need for personal cars (to facilitate commuting), exhibit a lower propensity to use on-demand transportation services and a lower propensity to own EVs (because of range and cost barriers). However, those in the highest income bracket exhibit a modestly higher inclination toward owning EVs (effect is statistically insignificant, but intuitive). Given the higher cost of EVs, this finding is consistent with expectations and the evidence to date in relation to EV ownership trends (e.g., Tal and Nicholas [*20*]).

Lowest income individuals embrace on-demand transportation services, while those with higher incomes are less likely to use on-demand transportation services—largely because they own personal vehicles and do not have a need to rely on shared mobility services. Once again, these findings are consistent with those reported in the literature (*32, 33*). However, there is some previous research that reports results contrary to this finding. A few studies have reported that high-income individuals are more frequent users of ridehailing services relative to low-income individuals (e.g., Tirachini and Río [*34*], Dias et al. [*35*]). A higher educational attainment is associated with a lower proclivity toward on-demand transportation usage. Long commuting distances are associated with lower levels of on-demand transportation service usage (because of high cost to travel long distances using such services) and lower levels of EV ownership (because of concerns about driving range). These findings are consistent with prior research (*36, 37*).

The joint model is found to offer a goodness-of-fit that is consistent with expectations for a model of this nature. In comparing the full log-likelihood of the joint model versus the null log-likelihood corresponding to a model with only thresholds, it is found that the specification significantly enhances fit with a resulting pseudo ρ^2 value of 0.16. The joint model exhibits an even greater improvement in log-likelihood value relative to a naive specification that neglects the endogeneity of the latent attitudinal constructs (essentially treating them as exogenous variables similar to socio-economic and demographic variables).

Study Implications and Conclusion

This paper is concerned with identifying factors that contribute to the adoption of on-demand transportation services and EV ownership in the Indian context, as the nation strives to move toward a sustainable transportation future. Using a unique survey data set collected in 2018 from a sample of 43,000 respondents spread across 20 cities in India, this paper develops a simultaneous equation model system to shed light on the factors that affect adoption of on-demand transportation services and EVs in India. In particular, not only does this paper consider the socio-economic and demographic variables that affect these behavioral choices, but the study places a special emphasis on understanding the important role played by attitudes, values, and perceptions in determining adoption of on-demand transportation services and EVs.

The model constitutes a simultaneous equations model with latent attitudinal constructs that are themselves endogenous and dependent on socio-economic and demographic variables. Thus, the model includes two endogenous variables of interest (adoption of on-demand transportation services and EV ownership), both of which are binary in nature. In addition, the model system incorporates two attitudinal constructs. One latent construct captures the car owning proclivity of the individual while the other latent construct captures the environmentally friendly lifestyle orientation of the individual. Each latent attitudinal construct is mapped to a pair of attitudinal indicator variables contained in the survey data set.

The analysis focuses on a random subsample of 2,972 respondents, all of whom report owning at least one car. It is found that only 7% of this subsample owns an EV, and only 9% use on-demand transportation services such as Uber and Ola. Thus, the uptake of these emerging mobility technologies remains quite low, and policies and interventions are needed to rapidly increase the adoption of these technologies. Within this subsample of car-owning individuals, 91% indicate that owning a car is important or very important. At the same time, however, 95% indicate that it is important or very important for their means of transport to be environmentally friendly. Just over one-half of this subsample believes that EVs will replace conventional vehicles by 2030. In other words, there is a strong interest and optimism in an environmentally friendly future of private transportation.

It is also found that EVs are largely owned by individuals in the highest income category (because of cost), and that certain groups such as females, employed individuals, and long-distance commuters are less likely to own an EV. This is very likely to stem from range anxiety and concerns related to the ability to recharge the EV battery when away from home in the middle of a trip.

Model estimation results suggest that subsidies and rebates for purchase of EVs may help enhance market adoption. Individuals outside of the highest income bracket report lower levels of EV ownership; therefore affordability is a key determinant of EV adoption and subsidies can help advance EV ownership among a larger segment of the Indian middle class. Second, cities across the country need to invest in charging infrastructure to alleviate range anxiety. As many residents in India may not be able to charge EVs at home (because of the nature of the housing unit, e.g., apartments), the ability to charge at the office, businesses, stores, restaurants, and other EV charging depots may go a long way in enhancing EV adoption. However, with increased adoption of virtual activities (e.g., e-shopping) and work from home during the COVID-19 pandemic, future research efforts should carefully consider the geographical redistribution of activity participation locations in identifying optimal placement of EV charging infrastructure.

Finally, it is found that attitudes and values significantly affect the use of on-demand transportation services and EV ownership. Shaping attitudes and values through information and awareness campaigns, free trial experiences, and real-world demonstrations may prove helpful in advancing more sustainable vehicular ownership choice and use. On-demand transportation services are gaining usage but are not necessarily sustainable unless the vehicles are battery powered and rides are shared. The simultaneous equations model estimated in this study shows that those who are more environmentally friendly in their lifestyle preferences are more likely than others to embrace both of these innovations. As such, information campaigns that bring about greater environmental friendliness and awareness among people would help motivate higher levels of adoption of on-demand transportation services (thus reducing reliance on privately owned vehicles) as well as ownership of EVs (if vehicle ownership is desired by the individual/household). It is also found that low-income individuals have higher propensity to use on-demand transportation, while high-income individuals exhibit a higher proclivity to own an EV. These results suggest that electrified ridehailing services may potentially address inequities in access to sustainable transportation technologies. Through the implementation of these mechanisms, coupled with investments in alternative modes of transportation that afford a high level of service (e.g., Metro systems, bus rapid transit, dedicated bus lanes), India can advance toward a future of sustainable transportation.

Several future research directions may be identified. Extensive model validation exercises need to be undertaken in future research efforts to assess the ability of models to predict adoption of transportation innovations in forecasting applications. Additional survey data should be collected to assess how the COVID-19 pandemic may have impacted attitudes, values, and lifestyle preferences in relation to mobility choices and activity engagement patterns. It would also be of value to explore the spatial transferability of models so that areas that do not have their own behavioral survey data may benefit from the application of models estimated using data collected in different contexts.

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Author Contributions

The authors confirm contribution to the paper as follows: study conception and design: S. Sharda, X. Ye, A. Raman, R. M. Pendyala, A. R. Pinjari, C. R. Bhat, K. K. Srinivasan, G. Ramadurai; data collection: A. Raman; analysis and interpretation of results: S. Sharda, X. Ye, A. Raman, R. M. Pendyala, A. R. Pinjari, C. R. Bhat, K. K. Srinivasan, G. Ramadurai; draft manuscript preparation: S. Sharda, X. Ye, A. Raman, R. M. Pendyala, A. R. Pinjari, C. R. Bhat, K. K. Srinivasan, G. Ramadurai. All authors reviewed the results and approved the final version of the manuscript.

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