Which pricing policy do road users accept?

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Road pricing remains one of the questionable concerns for transportation planners and researchers. However, the prerequisite for implementing road pricing is still user acceptability. The present study provides users' preferences for different road pricing schemes, which will help the researchers determine the optimum pricing schemes to adopt. We conducted a user acceptability survey to analyse their perceptions and acceptability of different road pricing schemes. Based on the questionnaire survey, a large-scale survey was conducted. However, with the varying toll charges and travel time savings from the alternatives, this study reviews the stated preference survey. The results from the developed multinomial logit model show significant differences in the choice of pricing scheme. The probability of supporting distance-based pricing is significant and it is affecting significantly. High occupancy toll emerged as the most acceptable by users with a perception of less travel time savings from using toll roads. However, the acceptance rate of dynamic toll pricing (DTP) increased among the users who opposed the current pricing scheme. Additionally, socio-economic variables had a major impact on the pricing scheme. The estimated parameter signs were logical and statistically significant. Further, the price elasticity was calculated for each pricing scheme, ranging from –0.45 to –4.80. The elasticities for DTP were greater when compared with other pricing schemes. The research outputs generated from this study will assist the practitioners working in a similar domain in developing various schemes and estimating their acceptance after implementation.

Keywords: Acceptability and preference, multinomial logit model, questionnaire survey, road pricing scheme, travel time and cost.

ROAD pricing is any fee or charge imposed on the users for using certain roads or areas. The policy of road pricing schemes is predominantly for generating revenue, road maintenance, financing, or as a management tool to reduce bottleneck conditions, heavy traffic jams and environmental impacts.

Keeping this aspect into consideration, various toll pricing schemes exist for the smooth operation and collection of toll fees like dynamic toll pricing (DTP), high occupancy toll (HOT), distance-based pricing (DBP), etc.[1]. HOT lanes permit small occupancy vehicles (SOVs) to ply by paying toll[2]. Dynamic pricing refers to variable tolls that vary with time or space to minimize the traffic during peak time in an optimum manner[3]. These technologies are well-developed and in use in different developed countries. However, implementing a pricing scheme requires user perception and the ability to pay, especially in developing countries.

In India, the processing time is high due to manual operation, causing traffic congestion and delays to the users[4]. Hence, the Government of India (GoI) has recently implemented electronic toll collection (ETC; also known as FASTag[5]) for compulsory payment of tolls on National Highways (NHs). Further, the toll collection system in India will switch to open road tolling in the future[6]. Hence, the present study aims to understand users' perceptions and acceptability of various pricing schemes in India and evaluate their willingness to pay toll fees across different pricing schemes.

Literature review

According to the literature review, various studies have attempted to understand the user perception and acceptability of pricing schemes (Table 1)[7–12].

Davidson *et al.*[13] conducted a stated and revealed preference survey to know the importance of toll route choice of the users when new pricing schemes are implemented. Some studies considered variables such as perception about toll amount and travel time savings for the users' willingness to pay toll[14,15]. Nikitas *et al.*[16] concluded that the attitudes of older people are distinctly different from the youngsters towards road pricing. Swami *et al.*[3] evaluated the viability of dynamic toll pricing in the context of a developing economy, and considered the Indian case using the same survey approach. They reported that the small car users were ready to shift for 25% discount rate.

The literature reveals that pricing schemes such as high occupancy vehicle (HOV)/HOT and the DBP and DTP cannot be applied in the Indian context. The present study aims to determine the user's acceptability of different toll pricing schemes in Indian conditions and the factors that affect the same.

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Table 1. Summary of the literature review

Reference	Study area	Modelling framework	Number of samples	Respondents
7	European cities	Stepwise multiple regression	954	Motorists
8	Leeds and London	Logit model	830	Uses of car, bus and other modes of transport
9	Taiwan	Mixed logit model	2339	Passenger car users
10	Jakarta	Bivariate response model	1998	Car users
11	India	Elasticity analysis, cost equation	Not applicable	Uses of car, bus, light commercial vehicle and heavy commercial vehicle
12	European countries	Structural equation modelling	284	Passenger car users

Table 2. Attribute levels for each alternative

Pricing scheme	Travel cost (INR)	Travel time savings (%)
Single occupancy vehicle (SOV)	65, 70, 80	5, 10
High occupancy toll (HOT)	60, 65	5, 10
Dynamic toll pricing (DTP)	50, 55, 60	2.5, 5
Distance-based pricing (DBP)	70, 80,90	10, 15

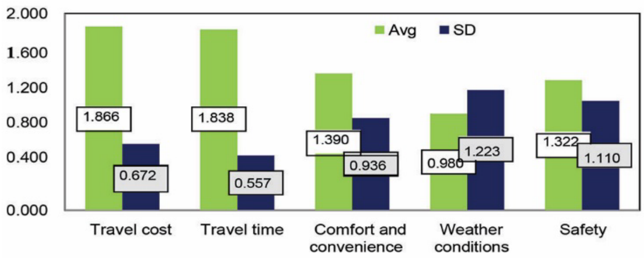

Figure 1. Evaluation of the attributes scale of –2 to 2.

Research methodology

The study focuses on users' perceptions of various road pricing schemes by developing a structured questionnaire. A response survey was conducted to project various preference data. According to the users' responses and choice preferences across different categories obtained from the questionnaire survey, the present study developed a multinomial choice model.

Questionnaire survey

Revealed data survey

Variables like gender, age and monthly income were initially included under the socio-economic category in the survey. The variation in the user's willingness to pay and attitude was the main reason for this[17]. Similarly, several travel-related observations were included in the next part of the survey, which comprised vehicle type, trip purpose, etc. Later, various attitudinal variables, like respondent choice and user perception, were considered in the scenario of a new type of pricing scheme. An in-depth literature review helped with regard to this.

Stated preference survey

In this survey, travel cost and time were the most critical attributes taken into consideration. The toll charge is the travel cost that a user pays as a toll fee. The distance-based tolling depends on the distance travelled. In order to capture the distance based pricings, hypothetical scenarios are considered with the base price of 50 INR (as 0.65 INR/km is chosen by National Highway Authority of India (NHAI), GoI, in order to decide the toll rates: PART II-Section 3.-Subsection (i)[18]) for a travel distance of 60 km (considering its length as a minimum of 60 km, and with some bridges and tunnels in between[18]). Thus, the travel cost is the multiplication of the per kilometre price with 60 km.

All the respondents were given four alternatives across the choice experiment design, which included DTP, SOV, HOT and DBP. A user can select an alternative based on the values of the attributes. Each attribute will have different levels. The basis for this information is taken from Jou and Yeh[9] (Table 2).

All the selected attributes were evaluated based on the 5-point Likert scale, where the perception varied from strongly disagree (–2) to strongly agree (+2). The observed values were corrected for leniency and central tendency errors. Figure 1 gives the calculated scores (Avg – average value; SD – standard deviation). The selection of attribute levels was done in context to the revealed data. Each combination had one particular level of the attribute. For the present study, to ensure mutually exclusive situations across the considered attributes, the orthogonal design was utilized[9]. The outcomes (relation between attribute and alternatives) revealed variance (70–90%) across responses. In this study, we used a fractional factorial design to minimize and remove the choice sets given to the users[19]. Accordingly, such choices were eliminated from the questionnaire. Hence, eight specific scenarios, including the user's peak and off-peak travel, were considered for this study.

The multinomial logit model (MNL) was used here to understand the factors affecting user acceptability of preferred pricing schemes. MNL is considered an upgraded version of the binary logit model that emerges as the preferred choice of researchers among the discrete choice models[11,20,21], where all log odd of outcomes are formulated as a linear combination for the predictor variables.

The general equation for MNL for choosing an alternative i ($i = 1, 2, \ldots, j$) from a set of j alternatives is given by eq. (1)

$$\text{Prob}(y_i = j) = \frac{\exp(\beta' X_{ij})}{\sum_{m-1}^{J_i} \exp(\beta' X_{im})}, \quad (1)$$

where y_i is the index of the choice made and $\beta' X_{ij}$ is the deterministic component of the utility function.

Data collection

Data were collected online by sending more than 1200 Google forms to the users. The online platform was preferred for car users due to the COVID-19 pandemic. Out of 1200 forms sent, 35% responded. The study region selected was near the Eethakota zone in Andhra Pradesh, India. During physical interactions and interviews conducted with the bus and truck drivers specifically, the required responses were collected at the lorry office, fuel pumps and hotels close to toll plazas following proper COVID-19 guidelines in December 2020. Some of the responses were taken from passenger car drivers in the field. It was found that there was no significant difference between the datasets; hence, they were combined.

Data from the bus and commercial vehicle drivers were intentionally collected through face-to-face interviews, as most of them are less educated. Also, the questionnaire was in the regional language rather than in English to get proper responses from them. The respondents had to select one alternative from those available in the case of the stated preference survey. Respondents were toll road users who were already being charged for using these roads. The data collection process included different types of vehicles both commercial and non-commercial, like buses, cars, light commercial vehicles (LCVs), heavy commercial vehicles (HCVs) and multi-axle vehicles (MAVs). A simple random sampling technique was used in the present study for the representative sample from the population for a face-to-face interview and a snowball technique for Google forms. Israel[22] has provided a simplified table to estimate the required sample. Considering a sample population greater than 100,000 and a precision level of 0.05, the approximate number of required responses was around 400 (ref. 23). In this study, a total of 750 responses were considered.

Data analysis

A total of 750 response data were collected using the questionnaire survey. There was no missing data in the collected responses. To evaluate the outliers appropriately, we utilized the Mahalanobis D^2 equation to generate the desired results[21]. Accordingly, a total of six outliers were captured for further evaluation. The adequacy, variable relationship and normality were well examined in the collected responses. The result of the Kaiser–Mayer–Olkin (KMO) test and Bartlett's test of sphericity was 0.860 and 0.000 respectively.

The primary evaluation of responses revealed that only 6% of respondents were female, whereas the others were male. The age-group classification revealed that 41.5% of the respondents were in the 30–39 age group, followed by 27.3% in the 21–29 age group. Majority of the respondents belonged to the income group less than 20,000 INR (54.60%). The highest education of respondents, viz. up to high school was 37%. Majority of the respondents were car (32.54%) and HCV users (28.68%). It was observed that most of the respondents pursued travel for work purposes (35.10%). Similarly, the commercial vehicle users were around 33.60%. Majority of the respondents had travelled more than 180 km (49.9%). Around 64.15% of the respondents had awareness regarding usage of toll roads. Also, 54.40% of the respondents reverted that the toll fares were high; however, they agreed that it saved travel time.

The chi-square analysis was carried out to check the significant association between two categories of variables. The null and alternative hypotheses are considered as follows. H_0 is the education and vehicle type (age/trip purpose) do not have any association (correlation). H_1 is the education and vehicle type (age/trip purpose) are associated (correlation).

The level of significance was taken as 0.05. The results showed that the P-value for all the cases was lower than 0.05, and hence, it can be concluded that education is strongly associated with vehicle type/age/trip purpose. Figure 2 shows the alluvial plots to strengthen these results. It can be seen from the figure that the heavy-vehicle drivers are mostly less educated or uneducated.

Figure 3 shows the acceptability levels of different pricing schemes from the preliminary observation of response data, under which users leaned more towards the acceptability of implementation of distance-based pricing (85%), followed by DTP (70%).

Model development

The MNL model was used to compute the effect of variables on the users' perceptions and individual choices of particular pricing schemes. The existing choice was considered a reference to determine the acceptability of other pricing schemes. Since the variables considered are categorical, the last category was considered the base case in the present study. For instance, the base case for the gender variable was taken as the female category. Parameter estimates of the MNL model are shown in Table 3, which presents coefficients of variables across 95% confidence levels appearing to be statistically significant. The related variables were analysed according to the logical significance of the coefficients and their P-value.

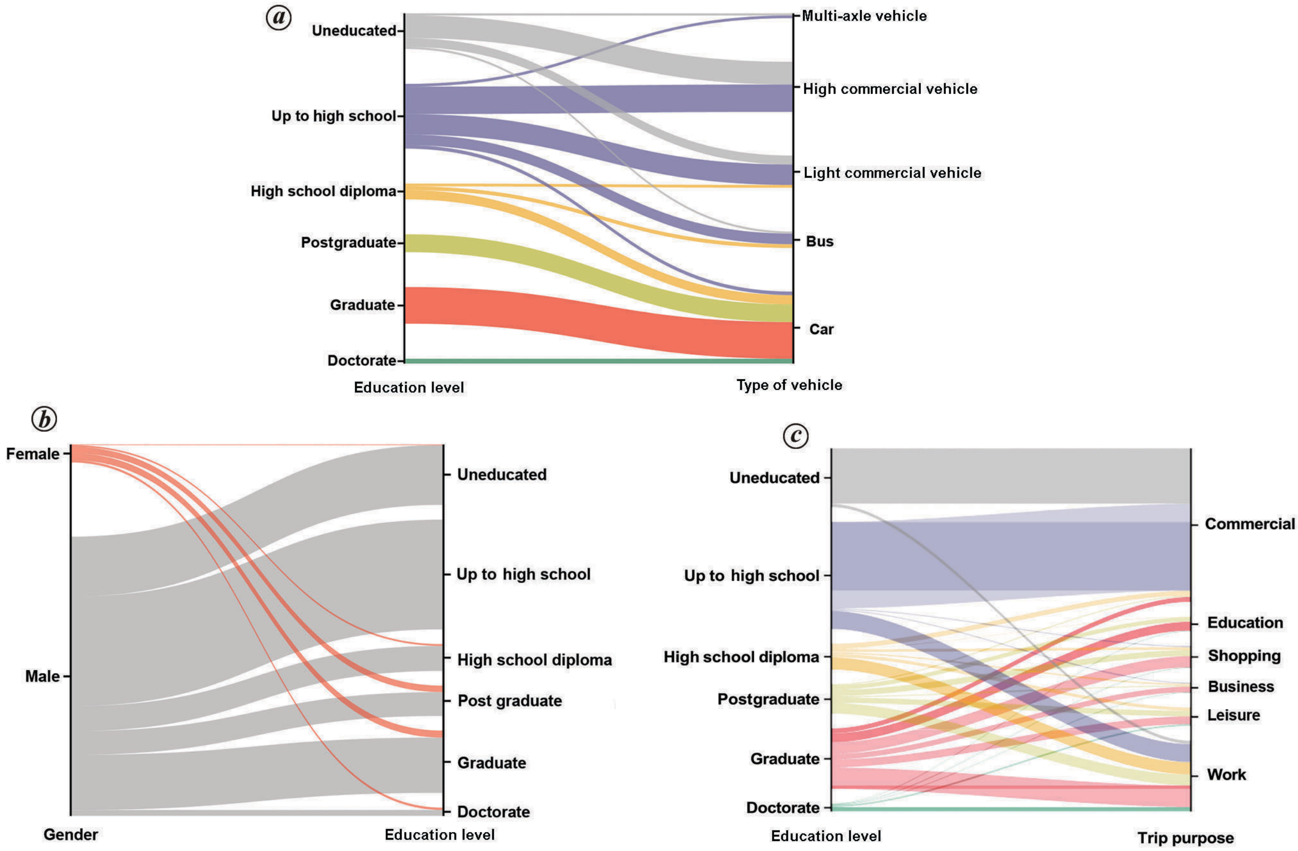

Figure 2. Alluvial plots: (***a***) Education and vehicle type, (***b***) gender and education and (***c***) education and trip purpose.

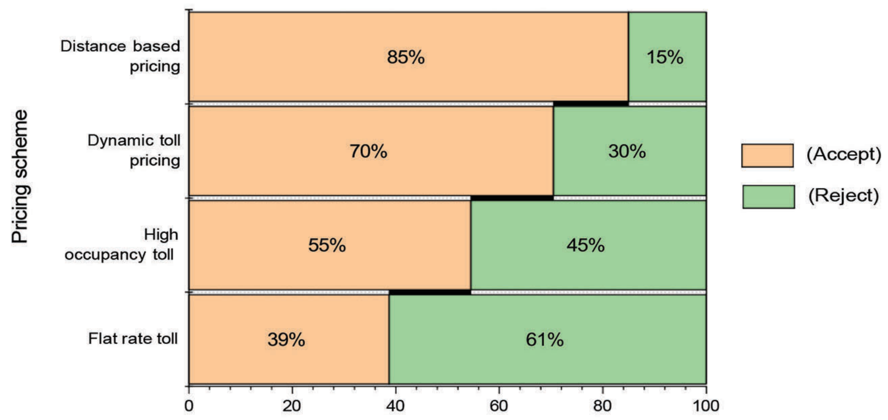

Figure 3. Summary of acceptability of pricing schemes.

The generic variables considered here were travel cost and travel-time savings, which significantly influenced user acceptability. The results of the analysis revealed that the respondents did not prefer to pay whenever the travel cost exceeds for any pricing scheme type. The results of the model for SOV showed that the acceptability towards implementation increased even with the increase in travel cost. This may be because the user wants to make a trip with single occupancy and has to pay a high toll. The higher travel time savings do not lead to more acceptability of SOV, as it is negatively affected. It can be seen that people in the younger age group are more willing to adopt SOV (coefficient = 3.375). SOV appears to be the preference among highly educated respondents. This can be understood by the fact that highly educated respondents diverge towards the aligned lanes and hence prefer SOVs. The model shows that the car users accepted SOVs for short distances. Attitudinal factors also had a significant impact

Table 3. Estimates of multinomial logit model

	SOV		HOT		DTP		DBP	
	Coefficient	Sigma	Coefficient	Sigma	Coefficient	Sigma	Coefficient	Sigma
Constant	0.806	0.000	0.683	0.000	0.238	0.213	0.598	0.000
Gender								
Male	–1.069	0.000	–0.055	0.849	–1.132	0.000	–1.547	0.000
Female (base case)								
Age group (years)								
21–29	3.375	0.000	1.251	0.08	0.856	0.064	1.824	0.000
30–39	2.519	0.000	0.313	0.051	0.163	0.684	–0.827	0.033
40–49	1.429	0.000	–0.257	0.429	0.326	0.423	0.326	0.040
50–59	1.342	0.002	–0.360	0.320	0.439	0.350	0.436	0.270
Over 60 (base case)								
Income level (INR)								
Below 20,000	–1.850	0.001	–1.970	0.000	–0.727	0.131	1.916	0.008
20,000–40,000	–1.147	0.013	–0.888	0.032	0.097	0.880	0.696	0.091
40,000–60,000	–0.614	0.123	–0.405	0.270	0.022	0.952	0.436	0.241
60,000–80,000	–1.487	0.001	–0.641	0.105	–0.088	0.818	–0.415	0.292
80,000–100,000	0.633	0.571	1.042	0.280	0.697	0.448	–2.325	0.011
100,00–120,000 (base case)								
Education level								
Uneducated	1.536	0.778	0.301	0.708	1.032	0.195	0.005	0.995
Up to high school	1.823	0.560	1.201	0.117	1.098	0.148	0.256	0.733
High school diploma	–2.162	0.084	–0.391	0.438	0.396	0.405	–1.092	0.028
Graduate	0.268	0.034	–0.686	0.082	0.699	0.063	0.069	0.008
Postgraduate	0.128	0.000	1.836	0.000	0.633	0.086	–1.643	0.000
Doctorate (base case)								
Type of vehicle								
Car	2.921	0.231	0.458	0.191	–0.415	0.707	–3.241	0.003
Light commercial vehicle	1.538	0.023	–1.448	0.683	0.519	0.644	–2.212	0.046
Bus	1.389	0.086	–0.252	0.720	–0.166	0.817	0.942	0.017
Heavy commercial vehicle	1.682	0.317	–0.032	0.955	–0.362	0.521	0.321	0.056
Multi-axle vehicle (base case)								
Trip purpose								
Work	0.644	0.057	–0.680	0.024	–0.580	0.055	–0.348	0.236
Education	2.805	0.000	–0.004	0.920	0.462	0.179	1.416	0.000
Shopping	1.712	0.000	–0.121	0.722	–0.588	0.080	–0.769	0.022
Leisure	2.821	0.000	0.657	0.082	–0.564	0.142	–0.234	0.516
Business	–0.566	0.000	–1.852	0.000	–1.369	0.001	0.999	0.015
Commercial (base case)								
Travel distance (km)								
45–60	1.732	0.000	–0.750	0.009	0.374	0.154	–0.782	0.006
60–90	0.774	0.003	–0.025	0.911	–0.415	0.058	0.182	0.420
90–120	0.059	0.085	–0.106	0.717	0.480	0.065	–0.107	0.698
120–150	–0.458	0.198	0.510	0.630	0.673	0.100	0.526	0.000
150–180	–1.385	0.855	0.702	0.570	1.382	0.000	1.035	0.004
More than 180 (base case)								
Awareness about toll roads								
Yes	–0.092	0.602	0.551	0.383	–0.131	0.000	0.034	0.820
No (base case)								
Opinion on toll rates								
Economic	1.426	0.000	1.680	0.000	0.996	0.052	–0.403	0.150
Reasonable	1.041	0.000	0.868	0.000	0.511	0.000	0.771	0.000
Expensive (base case)								
Opinion on travel time savings								
Yes	–0.710	0.047	–0.514	0.117	0.424	0.018	–1.126	0.001
No (base case)								
Travel time savings	–0.080	0.012	0.075	0.009	0.017	0.539	0.018	0.508
Travel cost	0.049	0.000	–0.023	0.046	–0.160	0.029	0.147	0.009

on SOV, as acceptance is higher for users who believe the current pricing system causes more delay and for users who believe toll rates are economical.

The positive signs of coefficients of higher income level categories show that users tend to shift to the HOT lane as income increases. The acceptability of HOT also changes significantly with respect to travel-related characteristics. The coefficient for vehicle type negatively affects commercial vehicle users because car users prefer HOT (44.39%). These findings show that those using toll roads with the car as the vehicle type lean more towards the managed lanes. Consequently, the acceptability of HOT is notably low for the respondents who observed that the existing one is useful for saving more travel time. However, the preference for HOT is more for lower travel costs, as the factor of travel cost has negatively correlated with use of HOT.

The model for exploring the acceptability of DTP results showed that attitudinal factors strongly influenced user perception. Among the socio-economic and travel-related characteristics, no logical significance was found in the categories of variables (age, income level, vehicle type), which were found significant in the above two pricing schemes. Long-distance trip users leaned more towards DTP. The acceptability of DTP was higher among the users who considered that the current toll system was not an appropriate mechanism for making funds.

In line with the preliminary analysis, the probability of supporting distance-based pricing is higher because almost all categories or subgroups of variables are statistically significant. These findings reveal that among the considered pricing schemes, acceptability is more for distance-based pricing irrespective of the characteristics of the respondents. The socio-economic characteristics and income level negatively affect the higher-income level groups because the truck drivers prefer this pricing scheme. Education also significantly affects the user acceptability of this pricing scheme. It is more acceptable for commercial vehicle-type users because they tend to travel more on toll roads. However, this pricing scheme does not significantly affect the opinion on toll roads but affects the perception of travel-time savings. Even with the increase in travel costs, this pricing scheme seems more acceptable.

The model was estimated to have a McFadden pseudo-R^2 value of 0.39, which falls within the acceptable range of 0.2 to 0.4. The current pricing scheme serves as the benchmark for comparison. Therefore, the coefficient is interpreted by comparing it to the best alternative available.

For model validation, the study considered 20% of collected responses for checking the accuracy of the estimated model. The prediction rate was around 74%, indicating good agreement between the user-chosen and model-predicted pricing schemes.

Predicted acceptance levels for different pricing schemes

The predicted acceptability levels for different pricing schemes with regard to travel cost and travel-time savings are discussed here. The percentages shown in the analysis are based on the observed frequencies from the sample that is considered. These findings indicate a difference in the acceptable levels for the variation of travel cost and time savings. The variation in acceptability shown in Figure 4 reveals that the predicted level of acceptability for distance-based pricing increases even when travel costs increase. As SOV and HOT were chosen by most higher-income group users, the acceptability increases with an increase in travel cost up to some value. However, in contrast with DBP, other pricing schemes show a decreasing trend. From these results, we can conclude that the majority of users would accept charge levels in the range 65–80 with travel-time savings of 5–10%.

Elasticity analysis and marginal effects

In this study, the elasticities of different pricing schemes with different levels of toll charge were determined and analysed to understand the impact of a unit increase in toll rate for each pricing scheme on the choice probabilities of each alternative. Price elasticity means change in demand with respect to change in price. This is especially useful in deriving policy insights for an increase in toll charges for each pricing scheme. For calculating the travel demand elasticities, the point elasticities were calculated[3] (Table 4).

The levels of toll rates were taken as those used in the stated preference study, and the elasticities were calculated. From the results, it can be observed that all the elasticity values are negative. An increase in toll rates results in a decrease in travel demand and vice versa.

The elasticities ranged from –0.45 to –4.80 for all the pricing schemes. The elasticities for DTP were more when compared to other pricing schemes, but they were negative. This implies that a maximum shift can be seen for DTP at lower prices, but as travel costs increase the shift decreases. The elasticity for SOV was –3.10 at a toll charge of INR 65, which indicates that with an increase of 1% of toll, the traffic changes by 3.10%. Similarly, the maximum elasticity for HOT was –3.90. In the case of distance-based toll, the elasticities were less when compared with other pricing schemes. This shows more acceptability of this pricing scheme compared to the others. This pricing scheme is general, i.e., it does not require any specific criteria related to time and occupancy. The differences observed in each pricing scheme were due to its applicability. The elasticity values in the present study were more than those reported in the literature[3,9]. Hence, the present price elasticity values will help policymakers and decision-makers fix toll charges for each pricing scheme.

Further, the cross-elasticities were found for all the modes using eq. (2), the equation considered by Iyenger and Gupta[24] as follows:

$$\rho_{kj} = \frac{\partial P(k)}{\partial \text{Travel cost}_j} \frac{\text{Travel cost}_j}{P(k)} = -P(j)\text{Travel cost}_j \beta_{\text{Travel cost}}, \quad (2)$$

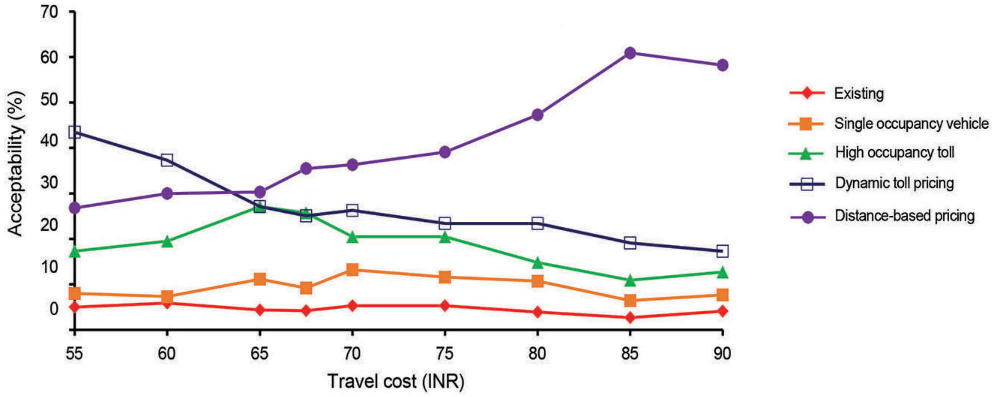

Figure 4. Plots of acceptability levels.

Table 4. Price elasticity

Pricing scheme	Toll charge (INR)	Elasticity
SOC	65	–3.10
	70	–2.20
	80	–1.58
HOT	60	–3.90
	65	–1.50
DTP	55	–4.80
	60	–2.40
DBP	70	–1.35
	80	–1.10
	90	–0.45

where ρ_{kj} is the cross elasticity of pricing scheme k that reflects the percentage change in the probability of choosing pricing scheme k with a 1% change in the travel cost of pricing scheme j. $P(j)$ is the probability of choosing scheme j and $\beta_{\text{Travel cost}}$ is the coefficient from the MNL model for travel cost.

Table 5 shows the results obtained. The results show that increasing the price of SOV by 1% decreases the probability of choosing the same by 3.46%. On the other hand, increasing the price of SOV negatively affects other pricing schemes. In contrast to SOV, HOT and DTP show an increase in the probability of choosing the schemes. The highest increase is for DBP with respect to DTP. Thus, elasticity analysis can reveal the effect of one pricing scheme on another, considering travel costs. Table 6 shows the marginal effects of each variable on the probability of choosing each system.

The marginal effects give the slope of the prediction equation at the given value of the independent variable. Thus, it shows the change in probability with a change in the unit value of the independent variable. It can be seen that gender has a negative marginal effect, indicating that males tend to accept any scheme more easily. The scheme shows that the age group between 30 and 39 years has the highest marginal effect for DBP (0.7381) compared to the other groups. A unit increase in travel-time savings increases the probability of using SOV by 0.0173 units. Similarly, travel cost also affects the probability. Thus, it can be seen that with an increase in a unit of travel cost, the probability of choosing SOV and DBP decreases while that for HOV and DTP increases. Therefore, different factors affect marginally the probability of acceptance of any scheme.

Conclusion

The present study aims to analyse the hypothetical adoption of four different road pricing schemes for users who use toll roads. From the extensive literature review, factors related to user perception and acceptability were considered. Based on these factors, a questionnaire was designed to determine user preferences towards these pricing schemes.

The results revealed that SOV, HOT, DTP and DBP were significantly affected by different variables. There was no common direction to be followed by the variables for each pricing scheme. The study outcomes also showcase that socio-economic factors have less impact on acceptability than attitudinal factors. DBP projects the highest acceptability rate compared to the others. The results of elasticity analysis show that the elasticity value of DTP is more, indicating the maximum shift observed in this scheme. The elasticity values obtained in this study will assist in computing the effective toll for these pricing schemes.

This study will be beneficial for transportation practitioners to correctly assess these pricing schemes before they are implemented. For successful implementation of these pricing schemes, the transport planners must promote and create awareness of particular pricing schemes. The study also indicates that user acceptability may vary with the existing conditions and the proposed pricing scheme. The research outputs generated from this study will assist the practitioners working in similar domains in developing various schemes and estimating their acceptance after implementation. The applicability of HOT for commercial vehicles, either for different strategies such as dedicated HOT for commercial vehicles or left-most lane for them, will be studied in future.

Table 5. Cross elasticity from the developed MNL model for travel cost

Change in travel cost of pricing scheme *j*	Scheme	Change in probability of pricing scheme *k*			
		SOV	HOT	DTP	DBP
	SOV	–3.465	–0.327	0.000	–3.920
	HOT	1.626	0.153	0.000	1.840
	DTP	11.313	1.066	0.001	12.800
	DBP	–0.626	–0.980	–0.001	–11.760

Table 6. Marginal effects for each coefficient

	SOV	HOT	DTP	DBP
Gender	–0.2566	–0.0124	–0.2689	–0.3661
Age (years)				
21–29	0.0003	–0.1252	–0.2013	–0.8538
30–39	–0.0012	–0.4205	0.1496	0.7381
40–49	0.0009	–0.1680	0.0956	0.0714
50–59	–0.3082	0.4178	–0.3601	–0.2963
Over 60 (base case)				
Type of vehicle				
Car	0.0033	–0.6593	0.3259	–0.0451
Light commercial vehicle	0.0133	0.3832	–0.3464	0.9471
Bus	0.0063	0.1535	–0.2057	–0.1006
Heavy commercial vehicle	–0.3082	0.0291	0.3295	–0.2226
Multi-axle vehicle (base case)				
Travel distance (km)				
45–60	–0.0135	0.1699	–0.2922	0.2694
60–90	–0.1855	–0.0629	0.4865	–0.1547
90–120	–0.4638	0.3481	0.1067	0.3683
120–150	–0.2617	0.0468	0.0499	0.0598
150–180	0.6891	–0.3207	–0.4400	–0.3517
More than 180 (base case)				
Awareness about toll roads	0.0200	–0.1101	0.0325	–0.0077
Opinion on toll rates				
Economic	0.0442	0.0043	0.0045	0.3461
Reasonable	–0.2560	–0.2539	–0.2198	–0.2495
Expensive (base case)				
Opinion on travel time savings	0.1673	0.1223	–0.1005	0.2742
Travel time savings	0.0173	–0.0165	–0.0042	–0.0082
Travel cost	–0.0104	0.0051	0.0397	–0.0329

In the present study, the travel cost and travel-time savings have been assumed to follow a linear relationship. In future studies, travel cost can be taken as a function of distance as cost per unit length. Further, this study's sample size is small to make policy decisions for the whole country, as it is a case study. Hence, it is recommended that the sample analysis be carried out with a larger sample size for country-level analysis.

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