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Does the Public Accept Congestion Pricing System in India in Developing Countries Context

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ABSTRACT: Traffic congestion is the major problem due to rapid urbanization and exponential growth of private vehicles, a decrease in the use of active transport, which results in problems of transport sustainability and public health issues. Generally, commuters often find it challenging to travel along the congested routes in urban areas due to increased travel time or air pollution. The traffic congestion of those congested routes may be minimized using strategies like congestion pricing, but public acceptability is one of the main hurdles in establishing a congestion pricing scheme. The present study attempted to understand the public acceptability of the congestion pricing system in India. To fulfil the objective of the study, a questionnaire survey was conducted to ascertain the public's perception of the congestion pricing system. In order to achieve this objective, a multinomial logistic regression (MNL) model was developed by considering public opinion on support to implement congestion pricing as a dependent variable, and other variables were considered as independent variables. From the model results, it is understood that the travel frequency (viz., 1-2 and 3–4 times) and number of times struck in congestion of commuters are most likely to remain neutral. The revenue generated by congestion pricing is allocated to road infrastructure, car tax reductions, public transportation, and parking areas, which are more likely to remain in neutral and under review after implementation. The study results are more useful to policy makers in urban areas while they relook at congestion pricing strategies in developing countries.

KEYWORDS: Congestion pricing; Public acceptability; Travel behaviour; Perception; Transport policies; Revenue allocations.

1. INTRODUCTION

Traffic congestion is the major problem due to rapid urbanization and exponential growth of private vehicles, a decrease in the use of active transport, which results in problems of transport sustainability and public health issues. Traffic congestion occurs on the road due to many factors, such as when the capacity of the road is not sufficient, and bottlenecks on the stretch of road. The increase in traffic congestion results in extra travel time for commuters, increased in fuel consumption of vehicles, an increase in vehicular emissions and a high vehicular accident rate. Common mitigation measures may increase roadway capacity, but it is difficult to cater to the construction of road infrastructure in urban areas to meet the increased traffic demand, which may result in additional congestion soon after (Wang et al., 2020). Hence, management strategies may provide the best possible solutions to meet the increase in traffic demand in order to minimize the congestion levels without additional roadway infrastructure. The few strategies of traffic management are parking prices and congestion or road pricing. Further, congestion pricing is one of the most efficient mitigation strategies to reduce traffic congestion in urban areas in developing countries like India. However, the pricing strategies, and public acceptability are the biggest hurdles in the implementation of congestion pricing strategies.

Congestion pricing remains one of the challenging issues for transportation researchers and planners in urban areas, particularly where there is a low acceptance rate. In congestion pricing, people should be encouraged to pay for external costs, such as air pollution, or they will have to change how and where they take public transportation (Bento et al., 2017; Barahona et al., 2020). It is an effective mechanism to achieve objectives such as relieving traffic congestion, environmental improvement, and revenue generation. However, the major hurdles of public acceptability of congestion pricing have to be understood before as well as after implementation based on the beliefs, perceptions, and attitudes of the public towards implementing congestion pricing. Congestion relief policies may boost the public's acceptance of congestion pricing schemes (Li and Zhao, 2017). Furthermore, acceptability is influenced by a variety of factors such as socioeconomics, people's travel habits, effectiveness, and revenue allocations. public might have different opinions about congestion pricing before as well as after implementation. Hence, these myths may help to motivate commuters to use public transport in the urban area (Moncada and Bocarejo, 2015; Gu et al., 2017). Moreover, implementation of congestion pricing in urban areas may change the commuter's attitude or behaviour in selection of their choice of destination, mode, and route, which may result in some congestion relief. There are added advantages of such a reduction in congestion in urban areas, including reduced delays of travelers, stresses of individuals, commuters in improving the vehicular speed, reliability, and sustainability of transportation and children's respiratory diseases (Borjesson et al., 2015; Simeonova et al., 2019). Based on congestion pricing, urban policymakers and transportation planners may increase revenue generation, allowing the government to invest more in public transportation.

The acceptability of congestion pricing by the public may vary based on the initial stage of implementation and the benefits received by commuters from congestion pricing over the time period. Congestion pricing has been implemented in many cities, and the lessons learned from the existing policies may be useful to transportation planners in making suitable strategies in order to overcome the acceptability hurdles for urban commuters. Generally, the congestion pricing studies indicate that the implementation of congestion pricing at the initial stage of the scheme is less acceptable by the public as compared to the time period. Studies have shown that during the initial day of operation, the accessibility of congestion pricing is less due to some unfavourable beliefs about congestion pricing by urban commuters (Zheng et al., 2014; Borjesson et al., 2015). However, the level of acceptance after the implementation may be increased because urban commuters may feel that the congestion pricing is effective to fulfil the targeted goals by considering the allocation of the raised funds to strengthen the road taxes (Levinson, 2010). In this view, transportation planners are more concerned about the factors on which congestion pricing depends and have identified some of these factors such as socio demographic factors, perceived effectiveness (viz., reducing traffic congestion and improving air quality), travel behaviour, attitude and social norms, equity issues and traffic management strategies. However, these factors might change from country to country because of the change in cultural and value of time corresponding to the individual's behaviour (Zmud and Arce, 2008). In this context, the present study has explored the factors that influence the congestion pricing system in India.

2. LITERATURE REVIEW

Congestion pricing is a potential scheme in order to discourage the use of personalized vehicles during the congested hours along the congested routes, but the public has their own choice to choose a mode as well as a route in democratic countries like India. There is extensive literature on public attitudes towards congestion pricing, which includes acceptance or support of public opinion in favour of implementation of congestion pricing. Hence, the acceptability of congestion pricing in such circumstances with varied commuter behavior, education level, and income levels is essential in the Indian context. The present study explores the various strategies adopted in the successful implementation of the congestion pricing system and the significant contributing factors to public adoption are explored based on the existing literature. Existing studies have shown that the following factors, such as effective congestion pricing, those who perceive negative externalities, and non-private mode users, were more favourable to the implementation of congestion pricing (Jaensirisak et al., 2005). The acceptability of congestion pricing was examined with various factors and results concluded that the major factors which influence opposition to congestion pricing are car users' unfavourable beliefs about the targeted goals, such as perceived effectiveness (Gaunt et al., 2007). Also, the literature has shown that congestion pricing is more likely to be acceptable when the outcomes of the congestion pricing policies are clearly stated and if the congestion policies address environmental concerns (Odeck and Bråthen, 2002). Studies have made conclusive remarks on the level of congestion charge for heavy vehicles, and a separate lane for trucks should be added on multilane highways (Kockelman et al., 2009). The level of acceptability of congestion pricing is influenced by personal characteristics, educational qualifications, perceived effectiveness of congestion pricing like value of time (VOT), and environmental aspects (Ubbels and Verhoef, 2006). Some researchers have found in Stockholm the importance of implementation of congestion pricing and it was concluded that the level of acceptance of congestion pricing is higher after implementation as compared to before implementation (Schuitema et al., 2010). Other studies have found that travel behaviour factors such as trip purpose and mode of choice have a significant impact on road pricing (Vrtic et al., 2010).

Further, researchers have identified that road pricing systems have significantly influenced the acceptability of congestion pricing (Dill and Weinstein, 2007) because the increase in complexity of pricing schemes was less comprehended by the public, which resulted in less acceptable (Vrtic et al., 2010). Analyzing the role of public attitude in the acceptability of congestion pricing has a significant role, and attitudes towards use of personalized vehicles with increased income level have higher impacts on the acceptability of congestion pricing (Rentziou et al., 2011). While others have found that travel costs after successful operation of a congestion pricing system are more attractive (Liu and Zheng, 2013). Some authors have examined whether the frequency of being stuck in traffic is the most significant factor in the public acceptability of congestion pricing in Shanghai (Chen et al., 2014). While researchers studied the income and trip purpose impacts on congestion pricing and found no significant impact on the acceptability of congestion pricing at the implementation stage (Rienstra et al., 1999), others concluded that socio-demographic variables have less impact on road pricing acceptability (Rienstra et al., 1999). women have a higher acceptability rate than men (Golob, 2001). Further, researchers have identified that public acceptability increases with revenue allocation of the raised funds from congestion pricing to improve road infrastructure (Liu et al., 2018). In developing countries, income level plays a major role in the acceptability of congestion pricing. However, existing studies show that there is no relationship between the higher income category of people and congestion pricing, and researchers strongly believe that income significantly contributes to congestion pricing (Dill and Weinstein, 2007). Studies have been conducted in developing countries to explore the perceived effectiveness and environmental aspects of congestion pricing (Liu et al., 2020). Also, studies have examined the public attitude towards socio-demographic factors, revenue allocation, and traffic management strategies in the acceptability of congestion pricing (Sunitiyoso et al., 2020). Studies have concluded that younger age groups of students and non-car-owning people highly accept the implementation of congestion pricing (Li et al., 2020). Several studies have investigated the differences in sociodemographic effects in terms of road pricing policy adoption between Japan and Taiwan (Jou et al., 2010; Tillema et al., 2005; Li et al., 2019). In addition, researchers studied the public acceptability of congestion pricing in Athens, Greece, using variables such as socio-demographics and perceptions of revenue allocation from road pricing (Anas and Lindsey, 2011; Jaensirisak et al., 2005; Agarwal and Koo, 2016). Researchers, on the other hand, have looked into how well people accept congestion pricing and how it affects things like electric vehicle policies (Bartley, 1995; Hao et al., 2013; Croci, 2016). In this regard, the current study was carried out in Hyderabad city to ascertain the public perception of the accessibility of congestion pricing in a developing country context.

3. METHODOLOGY

The proposed study adopted an online opinion survey to understand the contributing factors to the congestion pricing system and the commuters are certainly tolerable with the congestion pricing system in the Indian context.

3.1 Questionnaire Design

A questionnaire survey was initiated by reviewing the existing research in order to understand the factors which are already explored by the existing studies and which are suitable to understand the accessibility of congestion pricing by public perception in Hyderabad city, India. The preliminary survey was conducted based on the prepared questionnaire to explore the understanding of the questionnaire form by the public and transport experts. The ambiguity in the questionnaires was removed based on the initial structured questionnaire's suggestion for better clarity. The preliminary survey might improve the reliability of the collected data from the respondents. The questionnaire form consists of four sections, in which section one is related to the socio-demographic characteristics and the structured questionnaire is given related to the travel characteristics in section 2, commuters' perceptions in section 3, and attitudes towards congestion pricing, traffic management strategies, and revenue allocation given in section 4 respectively. The questionnaire form was prepared in English in Google Form for better distribution.

3.2 Data collection

The data was collected based on the mixed mode, both online and offline. To do online data collection, the commuters from Hyderbad city were considered from the educational institutes, the working commuters from both government as well as private firms, and people working in software companies. Offline data was collected using the same form, which was designed on a Google form, and the locations were chosen to be in high public demand areas such as metro stations, bus stops, and railway stations. Due to the pandemic, the offline survey was minimized and the emails were collected and distributed in the survey form through the collected emails and other social media networks. However, some of the responses of the respondents might be different due to the face-to-face interview as well as the online survey. In this process, a total of 620 samples were collected from both the online and offline methods. Further, the collected data was screened for complete responses, and the data was mined to eliminate these samples. A total of 538 sample sizes were used for the analysis. Figure 1 shows that respondents' support towards implementing congestion pricing as 58% and 21% of people are not supporting it, and 27.1% of respondents are neutral. However, these neutral people may shift towards the accessibility of congestion pricing based on the benefits received from the implementation of congestion pricing. Figure 1 also shows the perceived effectiveness variables of congestion pricing versus public opinion. 20% of people strongly agree that these variables are effective after implanting congestion pricing. And more than 80% of people sense that these variables are effective after the implementation of congestion pricing. Further, the received respondent data from the survey data collection is presented in Table 1, and the responses were given in percentage. Table 1 also comprises the structured questionnaire responses, which are considered on a 5-scale.

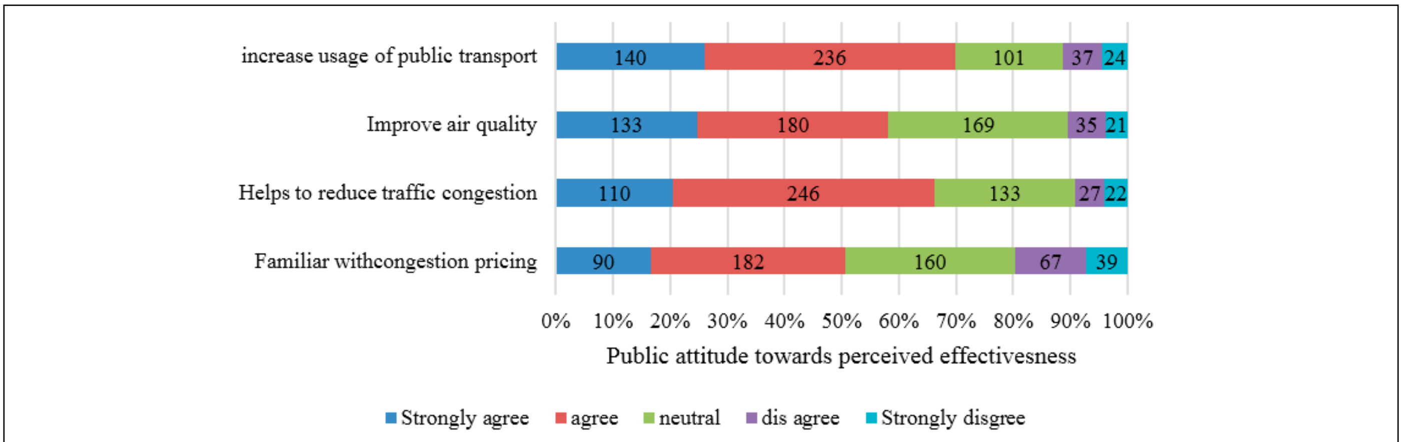

Figure 1. Public perception about congestion pricing and its effectiveness.

Factors	Options	Percentage (%)
Gender	A) Male	73
	B) Female	27
Age	A) 18 Y	1
	B) 19-34 Y	71
	C) 35-45 Y	15
	D) 46-555Y	12
	E)>56Y	1
Education	A) <secondary school (10+2)	5
	B) under graduate level	54
	C) post graduate level	41
Employment Status	A) Not working	10
	B) Housewife	4
	C) Retired person	2
	D) student	42
	E) working pvt company	27
	F) Govt employ	8
	G) Business	7

Household monthly income (in Rupees)	A) Not yet Earning	26			
	B) <10000	6			
	C) 10000-20000	12			
	D) 20000-30000	15			
	E) 30000-50000	16			
	F) >50000	25			
Number of Earning persons inHouse hold	A) 1	57			
	B) 2	31			
	C) 3	7			
	D) 4 and above	5			
Vehicle ownership	Vehicle ownership categories	0	1	2	Above 2
	A) Bicycle	70	25	3	2
	B) Two-wheeler	17	64	14	5
	C) Car	57	35	6	22
Do you have driving license	A) YES	26			
	B) NO	74			
Travel Frequency (in one week)	A) Never	4			
	B) 1-2 times	23			
	C) 3-4 times	16			
	D) 5-6 times	27			
	E) Daily	30			
Regular mode of choice	A) Bus	27			
	B) Auto	5			
	C) Own vehicle	52			
	D) Cab service	7			
	E) Metro	8			
	F) Sub urban train (MMTS)	1			
Distance travel in typical day (in kilometers)	A) 0-2	10			
	B) 2-10	31			
	C) 10-20	29			
	D) 20-30	19			
	E) >30	11			
Travel time in typical day (in minutes)	A) 0-10	5			
	B) 10-30	23			
	C) 30-60	43			
	D) 60-90	16			
	E) >90	13			
Monthly Travel cost (in rupees)	A) 0-1000	26			
	B) 1000-3000	42			
	C) 3000-8000	26			
	D) 8000-15000	4			
	E) >15000	2			
Vehicle usage per day	Frequency use of mode	0	1-2 times	3-5 times	>5 times
	A) Car	58	29	11	2
	B) Public transport	46	40	10	4
Purpose of your trip	A) Work	75			
	B) Shopping	13			
	C) Recreational activities	12			
No of times struck in trafficcongestion (in a week)	A) Never	4			
	B) 1-2	28			
	C) 3-4	32			
	D) 5-6	12			
	E) Daily	24			
General view of traffic congestionin Hyderabad	A) No congestion	2			
	B) mild	14			
	C) moderate	47			
	D) severe	37			

Following questions are 5 level questions. Choosing on a scale of 1-5 strongly Agree to Strongly Disagree 1-Strongly agree 2-Agree 3-Neutral 4- Disagree 5- Strongly disagree						
Scale		**1**	**2**	3	4	5
Congestion pricing be	A) Low-priced	39	26	23	8	4
	B) Reasonable	32	31	28	6	3
What should be the time of charge	A) During peak hour	52	30	11	3	4
	B) Throughout the day	8	10	36	22	14
What should be the method ofcharge	A) Fixed charge	12	21	39	18	10
	B) Distance based	24	44	19	7	6
	C) Time based charge	23	37	26	8	6
	D) Area based	24	29	30	10	7
Public opinion towards congestionpricing	A) Familiar with the concept ofcongestion pricing	16	33	31	12	8
	B) Help to reduce trafficcongestion	20	45	25	6	4
	C) Improve air Quality	24	33	31	7	5
	D) Increase usage of publictransport	26	44	19	6	5
Do you want to shift to given categories if they are exemptedfrom congestion pricing	A) Electric vehicle	41	35	19	3	2
	B) Odd- Even license platepolicy	22	32	36	7	3
	C) Public transport	44	29	21	4	2
Revenue allocations to	A) Road infrastructure	46	34	16	2	2
	B) Reduction of car tax	25	32	27	9	7
	C) Developing Public transport	48	32	14	4	2
	D) Developing parking area	42	34	16	4	4
	E) Creating wider pedestrianand bicycle lane	38	40	16	3	3
	F) Road side drain	41	35	17	3	4
Do you support the implementationof congestion pricing in Hyderabad	A) Support	52				
	B) Neutral	27				
	C) Not Support	21				

Table1: Descriptive Statistics

3.3 Model Formulation-Multinomial Logistic Regression model

The multinomial logistic regression model was developed by considering the dependent variable as the respondent's support for congestion pricing (viz., support, neutral, and not support). These were taken into account by converting strongly agreeing and agreeing to support and strongly disagreeing and disagreeing to non-support. There are three different models that were developed by changing independent variables, including socio-demographic as well as economic, behavioural, and travel-related factors. The theoretical model is given below in equation 1 to explore the probability of acceptance for congestion pricing. In the present study, the dependent variable was neutral to support and not support versus support, which is whether the public supports congestion pricing in three different cases (viz., Y = Support; Y = Neutral; and Y = Not-support). In this, two different logit models were developed, and the logit models are given in equation 2.

(1) $P(Y=1 \mid X\_1 = gender, X\_2 = age, X\_3 = Income \ldots)$

(2) $= \frac{(exp(\beta\_0+\beta\_1\,gen+\beta\_2\,age..\beta\_n\,Income))}{(1+exp(\beta\_0+\beta\_1\,gen+\beta\_2\,age..\beta\_n\,Income))}$

Further, the model 1 was developed based on the selected independent variables and includes socio-demographic as well as economic variables, which comprise the following variables: gender, age, education, employment, income, and vehicle ownership. A theoretical model is given which explores the probability of accessibility of the congestion pricing by the urban commuter as support, neutral, and not-support.

(3) $Log\ (odds\ of\ congestion\ pricing\ acceptance) = \beta 0 + \ 1 * gen + \beta 2 * age + \beta 3 * education + \ \beta 4 * employment + \beta 5 * income + \beta 6 * vehicle\ ownership$

The model-2 investigated the factors related to the respondent's travel behavioural factors, including travel frequency, mode of choice, travel distance and time per day, monthly travel cost, car usage, public transport usage, purpose of trip, number of times struck in traffic congestion in a week, and general view of traffic congestion in Hyderabad, which impacts on the acceptability of congestion pricing. Furthermore, the model-3 investigated the public attitude toward traffic strategies and revenue allocations (i.e., achieved through congestion pricing) such as improved public transportation, parking areas, air quality, type and timing of congestion pricing, revenue allocation to infrastructure as well as public transportation, parking areas, pedestrian lane, road side drain, reduction of car tax, and so on. Total samples of 538 respondent opinions were used in the multinomial logistic regression model. From this 538 sample, 80% of the data was used for the training and the remaining 20% of the data was used for the validation of the model in R-Studio software.

4. MODEL RESULTS

4.1 Socio demographic and economic variables impact on public support to implement congestion pricing

The multinomial logistic regression model was developed by considering the support to implement congestion pricing as a dependent variable and the socio-demographic as well as economic variables as independent variables. The chi-square value is 44.869 and the p-value of 0.000 of the calibrated models and the model results are presented in Table 2a and 2b. The Pseudo R-square value of the model is 0.27, and the log likelihood ratio is -371.63. Also, the overall prediction accuracy of the model is 52%. Based on the results of the model, it was found that there are 5 variables, including vehicle ownership, household income, and earning person, that are significant in the neutral versus support model. In the not-support versus support model, the higher education level was also significant.

Variables/Factor	Option	Coefficients (β)	Std error	Sig	Oddratio
Intercept		-13.834	0.616	0.001***	0
Education	Under graduation	0.333	0.873	0.170	1.395
	Post-graduation andhigher	0.575	0.867	0.120	1.778
Household monthly income(Rupees)	<10000	-0.302	0.536	0.140	0.739
	10000-20000	-0.583	0.432	0.040**	0.557
	20000-30000	1.231	0.434	0.001***	3.426
	30000-50000	-0.09	0.396	0.204	0.913
	>50000	0.154	0.4	0.175	1.166
Number of earning personsin house hold	2	-0.694	0.293	0.001***	0.499
	3	-0.234	0.511	0.160	0.791
	4 and above	0.582	0.876	0.120	1.791
Vehicle ownership of twowheelers	1	-0.422	0.344	0.040**	0.655
	2	-0.191	0.44	0.160	0.825
	2 and above	0.364	0.819	0.160	1.439
Vehicle ownership of Cars	1	0.165	0.293	0.140	1.179
	2	-3.091	1.126	0.001***	0.045
	2 and above	-20.204	0	0.001***	0
	Number of samples	538			
	Pseudo R-square	0.27			
	Log-likelihood	-371.63			
	AIC	827.26			

Note: *P<0.1, **P<0.05, ***P<0.01

Table 2a. Socio-Economic Variables Impact on Public Support to Implement Congestion Pricing (Neutral V/S Support).

Variables	Option	Coefficients (β)	Std error	Sig	Oddratio
Intercept		-0.977	1.417	0.122	0
Education	Under graduation	-0.609	0.804	0.112	0.543
	Post-graduation andhigher	-1.885	0.844	0.006***	0.151
Household monthly income(Rupees)	<10000	0.072	0.616	0.226	1.075
	10000-20000	0.114	0.467	0.201	1.121
	20000-30000	0.1539	0.477	0.001***	1.166
	30000-50000	0.168	0.475	0.18	1.183
	>50000	0.778	0.471	0.024**	2.179
Number of earning personsin house hold	2	-0.32	0.327	0.081*	0.725
	3	-0.222	0.618	0.179	0.8
	4 and above	1.25	0.837	0.133**	3.519
Vehicle ownership of twowheelers	1	-0.235	0.391	0.137	0.79
	2	-1.078	0.606	0.018**	0.34
	2 and above	0.323	1.021	187	1.381
Vehicle ownership of Cars	1	-0.405	0.359	0.064*	0.667
	2	-2.059	1.157	0.018**	0.127
	2 and above	-0.733	0	0.149	0
	Number of samples	538			
	Pseudo R-square	0.27			
	Log-likelihood	-371.63			
	AIC	827.26			

Note: *P<0.1, **P<0.05, ***P<0.01

Table 2b. Socio-Economic Variables Impact on Public Support to Implement Congestion Pricing. (Not Support V/S Support)

Variables	Response	Coefficients (β)	Std error	Sig	Oddratio
Intercept		1.434	1.3	0.067*	4.197
Driving license	Yes	0.311	0.301	0.075*	1.365
Travel frequency (in week)	1-2 times	1.142	0.926	0.054*	3.134
	3-4 times	1.563	0.978	0.027**	4.776
	5-6 times	-1.185	0.975	0.056*	0.305
	Daily	-1.803	0.958	0.014**	0.164
Travel distance in a day(kms)	02-10 km	-1.318	0.604	0.007*	0.267
	10-20km	-0.341	0.644	0.149	0.711
	20-30km	-1.192	0.71	0.023**	0.303
	>30km	-1.91	0.835	0.005***	0.147
Travel time in a day (inMinutes)	10-30 minutes	0.732	0.753	0.045**	2.081
	30-60 minutes	0.496	0.785	0.131	1.643
	60-90 minutes	0.285	0.845	0.183	1.33
	>90 minutes	0.328	0.909	0.179	1.388
Monthly travel cost (inRupees)	1000-3000	-0.437	0.329	0.045**	0.645
	3000-8000	-0.431	0.399	0.069*	0.649
	8000-15000	0.744	0.888	0.100	0.475
	>15000	-0.906	1.156	0.108	0.404
Number of times struck in traffic congestion (in week)	1-2 times	-2.872	0.125	0.002***	0.056
	3-4 times	-3.16	0.131	0.001***	0.042
	5-6 times	-2.937	1.174	0.003***	0.053
	Daily	-2.926	1.15	0.002***	0.053
	Number of samples	538			
	Pseudo R-square	0.20			
	Log-likelihood	-389.87			
	AIC	867.75			

Note: *P<0.1, **P<0.05, ***P<0.01

Table 3a. Travel Behaviour Variables Impact on Public Support to Implement Congestion Pricing. (Neutral V/S Support)

Variables	Response	Coefficients (β)	Std error	Sig	Oddratio
Intercept		0.587	1.37	0.167	1.798
Driving license	yes	1.179	0.401	0.001***	3.25
Travel frequency	1-2 times	0.031	0.947	0.243	1.031
	3-4 times	0.305	1.015	0.19	1.357
	5-6 times	0.128	0.996	0.224	1.137
	Daily	0.321	0.987	0.186	1.378
Travel distance in a day	02-10 km	-1.496	0.782	0.013**	0.224
	10-20km	-0.24	0.8	0.19	0.786
	20-30km	-0.449	0.839	0.148	0.638
	>30km	-1.02	0.929	0.068*	0.36
Travel time in a day	10-30 minutes	0.261	0.96	0.196	1.291
	30-60 minutes	1.041	0.982	0.072*	2.834
	60-90 minutes	0.901	1.029	0.095*	2.464
	>90 minutes	1.166	1.076	0.069*	3.209
Monthly travel cost	1000-3000	-0.541	0.394	0.042**	0.581
	3000-8000	-0.772	0.434	0.022**	0.461
	8000-15000	-2.119	1.159	0.016**	0.12
	>15000	-0.539	1.352	0.172	0.583
Number of times struck in traffic congestion (in week)	1-2 times	-2.418	1.207	0.011*	0.089
	3-4 times	-2.438	1.217	0.012**	0.087
	5-6 times	-2.269	1.252	0.017**	0.103
	Daily	-2.209	1.228	0.016**	0.103
	Number of samples	538			
	Pseudo R-square	0.20			
	Log-likelihood	-389.87			
	AIC	867.75			

Note: *P<0.1, **P<0.05, ***P<0.01

Table 3b. Travel behaviour variables impact on public support to implement congestion pricing. (Not support v/s Support)

Variables	Response	Coefficients (β)	Std error	Sig	Oddratio
	Intercept	-5.22	0.843	0.001***	0.005
Type of charge	Cheap	-0.276	0.132	0.009***	0.758
	Reasonable	0.081	0.155	0.15	1.084
Time of charge	During peak hour	0.239	0.181	0.046**	1.27
	Throughout the day	0.0844	0.152	0.145	1.088
Method of charge	Fixed charge	-0.067	0.148	0.162	0.934
	Distance based charge	-0.244	0.167	0.035**	0.782
	Area based charge	-0.193	0.156	0.054*	0.824
Perceived effectiveness	Reduce traffic congestion	1.038	0.219	0.001***	2.825
	Improve air quality	0.834	0.201	0.001***	2.303
	Increase usage of publictransport	0.437	0.206	0.001***	1.548
Traffic managementstrategies (exemptedfrom charging)	Electric vehicles	-0.016	0.199	0.233	0.984
	Odd and even policy	-0.126	0.171	0.114	0.88
	Public transport	0.442	0.177	0.003***	1.556
Revenue allocations	Road infrastructure	0.296	0.246	0.001***	1.345
	Reduction of car tax	0.241	0.155	0.031**	1.273
	Public transport	0.2	0.226	0.093*	1.222
	Parking area	0.437	0.188	0.005***	1.549
	Pedestrian and bicycle lane	-0.641	0.228	0.001***	0.526
	Road side drain	-0.602	0.214	0.001***	0.547
	Number of samples	538			
	Pseudo R-square	0.47			
	Log-likelihood	-317			
	AIC	714.019			

Note: *P<0.1, **P<0.05, ***P<0.01

Table 4a. Public Attitude Variables Impact on Public Acceptance of Congestion Pricing. (Neutral V/S Support)

Variables	Response	Coefficients (β)	Std error	Sig	Oddratio
Intercept		-6.725	0.972	0.001***	0.001
Type of charge	Cheap	-0.408	0.159	0.002***	0.664
	Reasonable	-0.114	0.18	0.131	0.891
Time of charge	During peak hour	0.001	0.21	0.248	1.001
	Throughout the day	0.014	0.179	0.234	1.014
Method of charge	Fixed charge	0.178	0.174	0.076*	1.195
	Distance based charge	-0.686	0.202	0.001***	0.503
	Area based charge	-0.221	0.187	0.059*	0.801
Perceived effectiveness	Reduce traffic congestion	1.218	0.251	0.001***	3.383
	Improve air quality	0.524	0.225	0.001***	1.688
	Increase usage of publictransport	0.871	0.224	0.001***	2.391
Traffic managementstrategies	Electric vehicles	0.083	0.222	0.177	1.086
	Odd and even policy	0.045	0.195	0.203	1.046
	Public transport	0.527	0.2	0.002***	1.694
Revenue allocations	Road infrastructure	1.031	0.277	0.001***	2.806
	Reduction of car tax	0.224	0.184	0.055**	1.251
	Public transport	0.094	0.25	0.176	1.099
	Parking area	0.196	0.213	0.089*	1.217
	Pedestrian and bicycle lane	-0.154	0.25	0.133	0.856
	Road side drain	-0.803	0.239	0.001***	0.447
	Number of samples	538			
	Pseudo R-square	0.47			
	Log-likelihood	-317			
	AIC	714.019			

Note: *P<0.1, **P<0.05, ***P<0.01

Table 4b. Public attitude variables impact on public Support to implement congestion pricing. (Not support v/s Support)

4.2 Travel behaviour related variables impact on public support to implement congestion pricing

Model 2 was developed based on the travel behaviour related factors and the results are summarized in Table 3a and 3b. These models were developed into two categories: neutral versus support and non-support versus support using R studio software. Support for implementing congestion pricing is regarded as a dependent variable, while variables related to travel behaviour are regarded as independent variables. The chi-square value is 41.277 with a p-value of 0.000, and the overall prediction accuracy is 50%, the pseudo R-square value is 0.20, and the log likelihood is -389.87. From Table 3a, six factors such as driving license, travel frequency, travel time, travel distance, monthly travel cost, and number of times struck in traffic had a significant impact on the public acceptability of congestion pricing. Whereas Table 3b summarized the results for non-support versus support conditions, the following variables were significant: driving license, travel time, travel distance, monthly travel cost, and number of times struck in traffic all contributed significantly to public acceptance of congestion pricing.

4.3 Public attitude on traffic strategies and revenue allocations related variables impact on public acceptance of congestion pricing

The third model was developed based on public attitude characteristics such as cost of congestion pricing, time of charge, method of charge, perceived effectiveness, traffic management strategies, and revenue allocation were considered as independent variables, and support to implement congestion pricing is considered as a dependent variable. The calibrated model results show that the chi-square value is 164.46 with a p-value of 0.000, and the overall prediction accuracy of the model is 68%. Also, the pseudo R-square value of the model is 0.47 and the log likelihood is -317.00. The model results are summarized in Tables 4a and 4b. From the model results, it is identified that the following variables, such as type of charge, time of charge, method of charge, perceived effectiveness, management strategies, and revenue allocation, have significant impact on the support for congestion pricing.

5. DISCUSSION

From the results presented in Table 2a, it is clear that there is no significant relationship between the education of a person when compared with their preference between "Neutral" and "Support" for implementing congestion pricing. From Table 2b, there is a significant relationship between the educational status of people and public support for congestion pricing in the model (not support versus support). The estimated odd ratios of not supported compared with the support to implement congestion pricing decreased by (1-0.55)*100=45% and 85% for a change from undergraduates to postgraduates. The result indicates that post-graduates are less likely to reject the congestion pricing than undergraduates and people below the undergraduate level category, and these results are confirmed by (Li et al., 2020). It may be due to the fact that the less educated level category may not understand the initial benefits of congestion pricing and might not support it. Table 2a and 2b show that household monthly income is a significant variable in studying the public's support for congestion pricing when comparing the choice between neutral versus support and not supported versus supported. The estimated odd ratios of neutral versus support are reduced by 26%, 46%, and 9% for income ranges of 10000, 10000-20000, and 30000-50000, respectively, and increased by 242% and 16% for income ranges of 20000-30000 and >5000, respectively. According to the above analysis, people of all income levels are less likely to remain neutral, with the exception of those earning Rs. 20,000- Rs. 30,000, who are more likely to remain neutral and observe the effectiveness of congestion pricing. Further, the estimated odds of not being supported compared with support increased by 1%, 12%, 16%, 18%, and 117% for income rages between <10000, 10000-20000, 20000-30000, 30000–50000, and >50000 respectively. So, people with less money are less likely to be against congestion pricing. This goes against what the study results (Kockelman et al., 2009) say about the relationship between income and public acceptance.

In developing countries like India, the income of the commuter might have a significant impact and the results need to be further explored with these income levels of para transit riders to determine whether they are ready to support congestion pricing in India. When compared to the neutral with support for congestion pricing, the estimated odd ratios are reduced by 51% and 21% for the categories of 2 and 3 earning people in a household, respectively, and increased by 79% for 4 and above earning people in a household. From the study results, the category of 4 and above earning people in a household are more likely to remain neutral in supporting congestion pricing. However, the present results were contradictory with the existing study results. It may be that more than 2 people in a household are not available in a developed country due to non-nuclear families or if the number of people earning in a household has to pay more for congestion pricing (Sunitiyoso et al., 2020). For vehicle ownership of two-wheelers, comparing the neutral with support condition, the odd ratio is decreased by 35% and 18% for one and two own two-wheelers and increased for two and above own two-wheelers by 44%. The study results suggested that people who have more than 2 two-wheelers are more likely to remain in neutral because these categories of people are less affected by the congestion pricing. The estimated odd ratio of the vehicle ownership of cars is compared between neutral and support, which is increased by 18% for only one own car person and decreased by 99% and 100% for two or more own car people. The study results observed that people having only one car are more likely to oppose congestion pricing, and people having less than two cars are more likely to remain neutral. However, the existing studies do not show any significant impact of car ownership on public acceptability of congestion pricing (Jaensirisak et al., 2005; Sunitiyoso et al., 2020).

From Table 3b, the odd ratio of a person having a driving license is 3.25, which indicates that the odds ratio increased by 225% when comparing the absence of support versus support of congestion pricing. It may be that the general population that holds a driving license might have a higher chance of vehicle ownership as a result, as cars result in more frequent trips by private vehicles, making them more likely to oppose the implementation of congestion pricing. which also indicates that people who have frequently used private vehicles are less likely to accept the implementation of congestion pricing. Travel frequency is one of the most important factors in understanding the public's support for congestion pricing. The estimated odd ratios are increased by 213% and 317% for the frequency of 1-2 and 3-4 times in a week and decreased by 70% and 84% for 5-6 and daily when relating to the neutral versus support choices and specify that frequently travelled people (viz., frequency having 1-2 and 3-4 times) are most likely to remain in neutral. Also, the odd ratios in two comparisons (Neutral v/s Support and Not support v/s Support) are significantly less, i.e., <0.1. Further, the estimated odd ratios are decreased by 99%, and all categories are less likely to remain neutral and less likely to oppose congestion pricing. Another important indicator is people stuck in traffic congestion without considering the number of times, and this category of commuters is more likely to support congestion pricing, and the results are supported by the existing research studies (Chen et al., 2014).

Also, existing studies have concluded that there is a reduction in travel related activities during peak hours due to congestion pricing (Rufolo and Kimpel, 2008). Moreover, the congestion cost (viz., type of congestion charge) odds ratios are decreased by 25% for cheap and increased by 8% for reasonable types of charges compared to the neutral versus support towards congestion pricing shown in Table 4. From the type of charge results, it is identified that the proposed reasonable congestion charges will make commuters more likely to remain in neutral. Furthermore, the estimated odds ratio increased by 27% and 9% during peak hour and throughout the day of congestion charging for the logit model case of neutral versus support towards congestion pricing, which indicates that the public is more likely to remain neutral. However, during peak hours, public opinion is more likely to accept congestion pricing when compared to throughout the day of congestion charging, see in Table 4. For the method of charge, the estimated odds are increased by 20% for the fixed method of charge and decreased by 50% and 20% for the distance and area-based charges, respectively. The association between not supporting versus supporting congestion pricing is strong. Hence, the study identified that the congestion pricing is implemented by the fixed charge of the opinion given by the neutral commuter are more likely to oppose the congestion pricing.

Also, the study identified that the perceived effectiveness has a significant impact on the support for congestion pricing by commuters. From Table 4, it looks like the odds of reducing traffic congestion, improving air quality, and getting more people to use public transportation are 182%, 131%, and 54% higher, respectively, than if people were neutral about congestion pricing. Existing studies show that the perceived effectiveness will significantly exceed the acceptability of congestion pricing by commuters due to the significant benefits received by the congestion pricing strategies (Sunitiyoso et al., 2020). Researchers have identified that effective communication strategies about the outcomes of congestion pricing may boost the acceptance of congestion pricing by the public (Kim et al., 2013; Hensher and Li, 2013; Gu et al., 2017). Also, for use of electric vehicles, the estimated odd ratios of not supported compared with supported are increased by 8%, 4%, and 70%. Furthermore, the odd and even vehicle policy is unpopular among commuters, and the exemption of public transportation from the congestion charge has a significant impact on the acceptability of congestion pricing. Hence, the study results indicate that the use of electric vehicles as well as odd-even license plate number policies are opposed by the public, which were considered the management strategies for implementation of congestion pricing when relating to the choice between neutral versus supported. However, existing studies show that there is a significant change in traffic volume due to odd-even number policies and an increase in public transit ridership due to congestion pricing strategies (Agarwal and Koo, 2016; Li and Guo, 2016). Moreover, the study results suggest that the revenue allocation to road infrastructure, reduction of car tax, public transport, and parking area of estimated odd ratios of not supported compared with supported is increased by 34%, 28%, 23%, and 55% and decreased by 48% and 55% for revenue allocation to pedestrian and bicycle lanes and road side drain. The revenue generated from congestion pricing is allocated to road infrastructure, car tax reduction, public transportation, and parking areas, indicating that commuters are more likely to remain neutral and review after the implementation of congestion pricing by comparing the initial benefits. These findings are supported by existing studies, which show that revenue allocation has a significant impact on the acceptability of congestion pricing (Sunitiyoso et al., 2020).

6. CONCLUSIONS

This study used a multinomial logistic regression model with three different models of socio-demographic, economic, travel behavior, and public attitude factors to look at how people feel about congestion pricing. The models were developed by considering public support towards implementing congestion pricing as the dependent variable as neutral versus support and not support versus support for congestion pricing. The study results concluded that the higher education category of commuters are more likely to accept congestion pricing because they realize the implementation of congestion pricing benefits such as reduced travel time and improved air quality. The study results also concluded that traffic management strategies such as exemption from congestion pricing while commuters use electric vehicles and odd-even policies are not supported by commuters in developing countries like India. Also, it is identified that the exception of public transport is more likely to be supported by commuters in India. Further, it is concluded that commuters who have a driving license are more likely to oppose the implementation of congestion pricing due to the more frequent use of personalized vehicles as compared to public transportation. All categories of income levels of the commuters are less likely to be neutral except the income category of Rs. 20000 to 30000 (viz., 268 to 400 USD) of the respondent's preferences of not supporting versus supporting congestion pricing. The study results observed that the four and above earning people in a household are more likely to remain neutral in supporting congestion pricing. Moreover, the study results concluded that commuters who have more than two two-wheeler vehicle ownership are more likely to remain neutral, whereas commuters who own only one car are more likely to oppose congestion pricing as compared to those who have two or more cars are more likely to remain neutral in the acceptability of congestion pricing.

The study observed that commuters who have a travel frequency of more than twice per week are most likely to remain neutral about the implementation of congestion pricing. It is also concluded that commuters who have been stuck in traffic congestion a number of times are less likely to oppose congestion pricing. Further, the study results estimated that the type of congestion charge and time of charge are more likely to remain in neutral during peak hours, whereas commuters are less likely to support congestion pricing throughout the day as a congestion charge. Perceived effectiveness factors like reducing traffic congestion, improving air quality and increasing usage of public transport are more likely to remain neutral. Furthermore, it is concluded that the revenue generated from congestion pricing, which is allocated to road infrastructure, reduction of car tax, public transport, and parking areas, is more likely to remain neutral. There are some limitations in the present study. For example, the present study does not show any significant impact of gender and age on the acceptance of congestion pricing where these factors were explored in existing studies. Also, the study is limited in data collection of the offline based data where the respondents' age group was skewed towards the younger age group and the income level of these groups is lower. Hence, further study is required to understand the elderly group's acceptability of congestion pricing in developing countries. Despite the fact that the study results do not conclude on the acceptance of congestion pricing by paratransit drivers such as autorickshaw and ride-hailing drivers in developing countries, of these limitations, the study results provide insights into factors such as vehicle ownership, congestion charging schemes, and travel-related attitudes on the acceptability of congestion pricing. The present study results may be useful to urban policy makers in order to understand the acceptance of congestion pricing in developing countries by urban commuters.

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