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RESEARCH ARTICLE

Binary Logistic Model for Estimation of Mode Shift into Delhi Metro

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Abstract: This paper aims to study the public transport mode choice behaviour of commuters in Delhi so that appropriate strategies to incentivize the use of public transport can be developed. We examine the efficacy of a multivariate statistical modelling approach to predict the probability of non-metro commuters to shift to the Delhi metro. We also analyse the reasons for this shift from private motor vehicles (PMVs) and buses. Data is collected through a survey of the metro commuters over various metro lines. A binomial logistic regression model is formulated to predict whether existing metro users have shifted from buses or are new additions to public transport shifting from PMVs. The model is validated well through several methods. The model analysis reveals that 57% of the metro users have shifted from buses and 28.8% from PMVs. The shift is more amongst females than males.

1. INTRODUCTION

The National Capital Territory (NCT) of Delhi is the largest city in India with a population of about 17 million at present [1] and is expected to be 24 million by 2021. The primary reason for this enormous growth is that Delhi is the National Capital and provides for attractive commercial avenues as well as better health and education facilities [2, 3]. With increase in population, the number of private motor vehicles (PMVs) plying on Delhi roads have also increased from 5.36 lakh in 1981 to 88.27 lakhs in 2014 [4]. All this growth and expansion comes with big issues around mobility. On an average 48,621 cars and 99,340 two-wheelers (2Ws) were added annually to the Delhi roads from 1991-2000, and the respective numbers have increased to 114,386 and 187,065 in the last decade (2001-2010). According to the latest available data, the number of additional cars and 2Ws per year are 153,916 and 310,617 respectively [4]. Further, the number of cars have been growing at higher rates than of 2Ws [5, 6]. A recent WHO report revealed that the pollution level in Delhi is three times higher than the level prescribed by WHO and is continuously increasing [7]. Thus, there is a strong need to shift people from PMVs to public transport. This is only possible by making public transport as attractive as PMVs.

Therefore, there has been a growing interest among policymakers about the relevance of rail-based systems in India to address the mobility needs of the ever expanding population in the cities. While evaluating different mass transit options for Indian cities, metro systems are often given priority due to the belief that road-based bus systems cannot cater to capacity requirements as much as metro systems [8]. Sreedharan [9] also predicted that by the end of 2007, the metro will be able to take the load of 40,000 PMVs. Also, the Delhi metro is in line with rapid transport systems globally, and as a result, is a welcome step in the popular perception.

However, there is a need to determine whether the shift to metro happened from PMVs or existing public transport such as buses. Various passenger mode choice models have been developed [10 - 12] in the literature, but no work, to the best of our knowledge has attempted to study this cannibalization effect in Delhi, *i.e.* the shift of commuters from one mode of public transport (buses) to the other (metro). Thus, an objective of the research is to develop a mode choice

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model to estimate the mode used by the metro commuters before the commencement of metro services. We also analyse the factors that encourage commuters to opt for the metro as their preferred mode of commute. The paper also develops a binary logistic model to predict the probability of non-metro commuters of a given profile shifting to the metro.

2. SURVEY DETAILS

2.1. Study Area

The area targeted for the survey covers six stations of the Delhi Metro namely Hauz Khas (HK), Chandni Chowk (CC), Rajeev Chowk (RC), Kashmere Gate (KG), New Delhi (ND), and Central Secretariat (CS) (Fig. **1**). The HK station is selected for a pilot survey to gain specific insights and make subsequent main survey more meaningful. For the main survey, the top five revenue generating stations are chosen (Fig. **2**). The choice of these five stations constitutes a representative set for the following reasons. In addition to high revenue generation, CC and ND connect Delhi's main stations of the Indian railways network. KG connects the main station of the interstate road transport network. Moreover, RC and CS are major interchange stations of the Delhi metro.

Fig. (1). Map of study area.

2.2. Experience of Pilot Survey

A pilot survey is conducted at the HK metro station before the main survey to gain experience and refine the questionnaire based on this experience. The pilot survey enhanced the main survey in the following ways:

2.2.1. Problem of Non-responses

The problem of non-response is faced in the pilot survey owing to the long initial questionnaire. The final questionnaire is designed to keep the response collection time less than two minutes. It enables easy interpretation of questions by the metro users at the metro stations and the interest of respondents remains alive.

2.2.2. Poor Initial Survey Design

The initial survey was earlier designed for more information than required for the objectives of the paper. After the pilot survey, learning from its experience, the instrument is redesigned to get only the relevant information.

2.2.3. Clear Questions

The initial survey design was found to lack clarity on the questions as perceived by the respondents. This was addressed in the final survey.
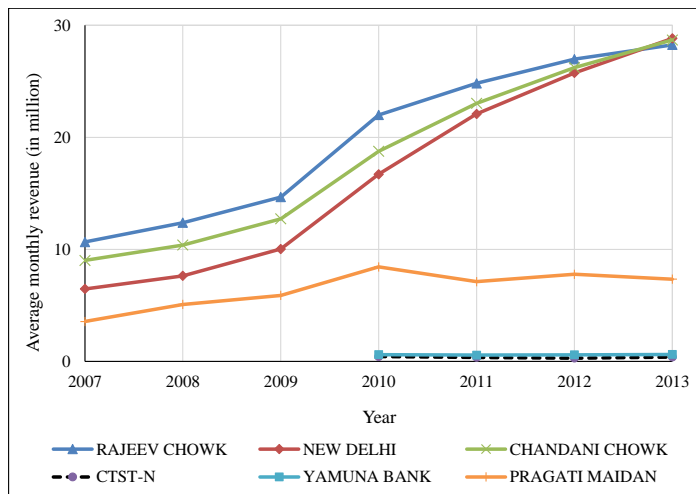
Fig. (2). Maximum and minimum revenue stations.

Table 1. Percentage of metro users in each group.

Profile		KG	CC	ND	CS	RC	Overall %
				Metro stations			
Age group	< 25 years	44	48	59	60	51	52.4
	25-40 years	48	37	25	34	35	35.8
	41-55 years	5	11	14	5	11	9.2
	> 55 years	3	4	2	1	3	2.6
Income	< Rs 10,000 (US$ 150)	21	9	2	5	4	8.2
	Rs 10000-30000 (US$ 150-450)	40	40	35	33	33	36.2
	Rs 30000-50000 (US$ 450-750)	20	27	28	32	28	27
	> Rs 50000 (US$ 750)	19	24	35	30	35	28.6
Occupation	Govt. Service	12	15	16	14	13	14
	Pvt. Service	46	44	35	34	39	39.6
	Business	14	14	13	12	14	13.4
	Student	24	27	36	40	33	32
	Unemployed	2	-	-	-	1	0.6
	Others	2	-	-	-	-	0.4
Vehicles ownership	Car	33	32	35	38	37	35
	Motorcycle	42	35	25	32	36	34
	Bicycle	3	4	1	4	3	3
	Others/None	22	29	39	26	24	28
Mode before Metro	PMV	28	28	32	28	28	28.8
	Bus	51	68	59	48	59	57
	Auto/Taxi	8	2	3	11	8	6.4
	Others/None	13	2	6	13	5	7.8

2.3. Final Survey Report

The survey is planned to get responses for the profile of the metro users and their reasons of shifting to the metro either from buses or PMVs. The profile information, presented in Table **1**, includes age, income, gender, occupation and vehicle ownership of metro commuters, and their modes of commute prior to using the metro. The questions that correspond to the reasons of shifting to the metro are shown in Tables **2** and **3**.

Table 2. Reasons of shifting to metro from PMVs.

Type of Responses	Metro stations					
	KG	CC	ND	CS	RC	Overall
	It is cheaper to travel in Metro than in own vehicle (%)					
Yes	41	22	25	35	30	30.6
No	4	5	-	3	3	3
Maybe	3	5	7	3	3	4.2
	It takes lesser time to travel in Metro (%)					
Yes	47	29	29	36	33	34.8
No	1	-	-	3	1	1
Maybe	-	3	3	2	2	2
	There is lots of traffic and congestion on roads (%)					
Yes	47	29	30	39	34	35.8
No	1	3	2	2	2	2
Maybe	-	-	-	-	-	-
	It is safer to travel in Metro than in own vehicle (%)					
Yes	42	17	21	33	26	27.8
No	2	7	5	6	4	4.8
Maybe	4	8	6	2	6	5.2
	To reduce pollution due to own vehicle emission (%)					
Yes	33	13	17	28	22	16.6
No	7	11	8	7	6	7.8
Maybe	8	8	7	6	8	7.4
	No stress of driving (%)					
Yes	44	20	22	27	27	28
No	4	9	8	11	8	8
Maybe	-	3	2	3	1	1.8

Table 3. Reasons of shifting to metro from buses.

Type of Responses	Metro stations					
	KG	CC	ND	CS	RC	Overall
	It takes more time to travel in a bus (%)					
Yes	46	64	42	53	56	52.2
No	1	2	14	2	2	4.2
Maybe	-	1	9	3	2	3
	There is no direct bus service (%)					
Yes	21	41	42	41	32	35.4
No	21	18	14	10	21	16.8
Maybe	5	8	9	7	17	9.2
	Buses are not punctual (%)					
Yes	19	23	21	32	21	23.2
No	21	33	34	20	29	27.4
Maybe	7	11	10	6	10	8.8
	Buses are very crowded (%)					
Yes	27	31	39	44	34	35
No	18	30	19	11	22	20
Maybe	2	6	7	3	4	4.4
	Buses are not safe and secure (%)					
Yes	31	29	33	32	41	33.2
No	12	22	20	16	12	16.4
Maybe	4	16	12	10	7	9.8
	Bus stop is more than 400m (%)					
Yes	9	10	33	23	12	17.4
No	30	52	20	31	42	35
Maybe	8	5	12	4	6	7

2.3.1. The Profile of the Metro Users

The survey is conducted among a total 500 respondents. It is revealed that more than 88% of metro users are below 40 years of age (mostly young people). Only 8.2% have a monthly income less than Rs 10000 (US$ 150) while more than 55% commuters have a monthly income more than Rs 30000 (US$ 450). Most of the metro users are either employed or students. The analysis also reveals that 28.8% of the metro commuters used their own vehicle prior to using to metro, whereas about 57% used buses. Moreover, about 72% of the metro commuters have their own vehicles. The detailed results related to the profile of metro users are presented in Table **1**.

2.3.2. Reasons for Shifting to Metro

The commuters are divided into two categories based on their responses in the first part: i) those shifted from PMVs and ii) those shifted from buses. The top six reasons for this shift are identified for each category from the pilot survey done at HK metro station. For a given category, and each reason corresponding to the category, commuters are asked if the reason is applicable to them for shifting to the metro. Commuters can respond with a "Yes", "No" or "Maybe" and Tables **2** and **3** present the percentage for each of the responses. The top three probable reasons for the shift are:

For people shifted from PMVs:

- There is a lot of traffic and congestion on the roads.
- It takes lesser time to travel in Metro.
- It is cheaper to travel in Metro than in own vehicle.

For people shifted from Buses:

- It takes more time to travel in a bus.
- There is no direct bus service.
- The buses are very crowded.

3. MODE CHOICE MODEL AND ANALYSIS

Pavlyuk and Gromule [13] perform an econometric analysis of the behaviour of bus and train passengers and their choices between different transportation modes using the Nested discrete choice model. To model the mode behaviour of car and bus use, a study [14] is conducted in Tripoli, Libya (which has high car ownership) using a binary logistic model. The results show that some measures have to be taken to encourage car users to use other forms of public transport. Transit Oriented Developments (TODs) are often designed to promote the use of sustainable modes of transport and reduce car usage. The effects of personal and transit characteristics on travel choices of TOD users can be investigated using binary logistic regression models. One such model is developed to determine the probability of choosing sustainable modes of transport including walking, cycling and public transport at Brisbane, Australia [15].

The Binary Logistic models reveal that personal and transit characteristics have an impact on the decision of mode selection [16, 17]. One of the most critical issues in travel behavioural modelling is to select the most appropriate mode of daily commute [17]. The quantification of this interaction in terms of mathematical relationships is known as modal split and the travel demand models are referred to as modal split or mode choice models. Stated preference survey is conducted to forecast travel behaviour in a hypothetical travel environment whereas the revealed preference survey is used to study the current travel behaviour [16]. To reflect the travel characteristics of the targeted population, precise data is collected from this survey and used as an input to the logistic regression model developed to predict mode shifts.

In this paper, a binomial logistic regression model is formulated to predict whether existing metro users have shifted from buses or are new additions to the public transport system, having shifted from PMVs. The mode shifted from is used as the categorical dependent variable and is correlated with categorical and continuous independent variables responsible for the shift. More details of the model are presented in section 3.1.

3.1. Logistic Regression Model

In this section, a binary logistic regression analysis is applied to predict the, mode a given metro commuter has shifted from. The predicted values are PMVs (0) and buses (1). A total of five explanatory variables are considered out of which two are categorical and three are quantitative in nature. The details of the explanatory variables are as follows:

Categorical Variables

Gender (Male/Female) X_1

(Coded as 1 for Female and 0 for Male)

PMV Owned (Yes/No) X_2

(Coded as 1 for Yes and 0 for No)

Quantitative Variables

Ingress distance to the Metro (Km) X_3

Age (Years) X_4

Income (in thousands per month) X_5

Let p is the probability that the mode used prior to metro was a bus and B_i (i=0, 1, 2, 3, 4, 5) are coefficients of the Binary Logistic Regression model to be estimated from the data. Then according to standard theory of logistic regression [18], the value of Logit is given by:

$$L= ln\ (odds) = ln\ (p/1\text{-}p) = B_0 + B_1X_1 + B_2X_2 + B_3X_3 + B_4X_4 + B_5X_5 \tag{1}$$

$$L= B_0 + B_1*Gender + B_2*Vehicle\ ownership + B_3*Ingress\ Distance + B_4*Age + B_5*Income \tag{2}$$

The model analysis is done using SPSS software and the output is given in Table **4**.

Table 4. Variables in the logit equation.

	B	**S.E.**	**Wald**	**Df**	**Sig.**	**Exp(B)**
Vehicle (0)	1.405	.273	26.566	1	.000	**4.075**
Access	.008	.035	.058	1	.810	1.008
Age	-.008	.010	.640	1	.424	.992
Income	-.023	.007	9.671	1	.002	.977
Gender (1)	.617	.320	3.721	1	.054	**1.854**
Constant	1.150	.397	8.378	1	.004	3.159

The equation of the logistic regression line is given by:

$$L = ln\ (odds) = ln\ (p/1\text{-}p) = 1.150 + .617X_1 + 1.405X_2 + .008X_3 - .008X_4 - .023X_5 \tag{3}$$

The two variables having the highest effect on the logit (log of odds of using a bus prior to the metro) are vehicle owned and gender. From Table **4**, two observations stand out: Commuters not owning a vehicle are almost 4 times more likely to shift to the metro from buses compared to people owing a vehicle (Exp(B) for vehicle (0) = 4). Similarly, females are almost twice more likely to have shifted from buses to metro than the male counterparts (Exp(B) for gender (1) = 1.8).

3.2. Logistic Regression Model for Different Stations

The binary logistic regression analysis discussed in section 3.1 is then is carried out for all the five stations separately. The resultant equations are given as (4), (5), (6), (7) and (8) respectively for KG, CC, ND, RC and CS respectively. The significant coefficients corresponding to each station are highlighted in **bold** in the following equations:

$$L = ln\ (p/1\text{-}p) = -0.477 - \textbf{0.211}X_1 + \textbf{1.043}X_2 + 0.175X_3 - 0.012X_4 - 0.002X_5 \tag{4}$$

$$L = ln\ (p/1\text{-}p) = 3.069 + \textbf{1.842}X_1 + \textbf{1.770}X_2 + 0.004X_3 - \textbf{0.026}X_4 - 0.056X_5 \tag{5}$$

$$L = ln\ (p/1-p) = 1.408 + \mathbf{\mathit{2.997}}X_1 + \mathbf{\mathit{1.778}}X_2 - \mathbf{\mathit{0.030}}X_3 - \mathbf{\mathit{0.026}}X_4 - 0.019X_5 \qquad \textbf{(6)}$$

$$L = ln\ (p/1-p) = 0.820 + \mathbf{\mathit{1.782}}X_1 + \mathbf{\mathit{1.948}}X_2 + 0.024X_3 - 0.013X_4 - \mathbf{\mathit{0.027}}X_5 \qquad \textbf{(7)}$$

$$L = ln\ (p/1-p) = 2.027 + \mathbf{\mathit{0.432}}X_1 + 0.600X_2 + 0.024X_3 - 0.016X_4 - \mathbf{\mathit{0.043}}X_5 \qquad \textbf{(8)}$$

The main findings of this analysis are; i) Females are generally more likely to have shifted from buses to metro than the male counterparts. The same is strongly evident from the analysis of CC, ND, RC and CS data (Exp(B) for female varies from 1.54 for CS to 20 for ND). ii) Commuters not owning a PMV are much more likely to shift into metro from buses than commuters owning a PMV (Exp(B) varies from 1.822 for CS to almost 7 for RC metro station data).

4. VALIDATION AND MODAL SPLIT

In this section, the results of the logistic regression model are validated using three methods to conclusively demonstrate a good fit and validity of the model. Further, a vehicle ownership split model is developed to get better insights on how the PMV type influencing mode shift to the metro.

4.1. Model Validation

The model is validated using three methods, namely; classification table, receiver operating characteristic (ROC), and cross-validation and their details are presented in section 4.1.1-4.1.3.

4.1.1. Classification Table

Table **5** shows that this model allows to correctly classify 96 / 183 = 52.5% of the commuters earlier using PMVs. We also see that the model correctly classifies 269 / 317 = 84.9% of the commuters earlier using buses. Overall 365 predictions are correct out of 500 times, for an overall success rate of 73% which is well within the acceptable range [19].

Table 5. Classification table.

Observed		Predicted		
		Mode		Percentage Correct
		0	1	
Mode	0	96	87	52.5
	1	48	269	84.9
Overall %				73

4.1.2. ROC Curve

A measure of goodness-of-fit often used to evaluate the fit of a logistic regression model is based on the simultaneous measure of the sensitivity (True positive) and specificity (True negative) for all possible cut-off points. First, we calculate sensitivity and specificity pairs for each possible cut-off point and plot sensitivity on the y axis Vs (1-specificity) on the x axis. This curve is called the receiver operating characteristic (ROC) curve. The area under the ROC curve ranges from 0.5 and 1.0 with larger values indicative of better fit. The area under the curve for the model developed in this paper is .723 (Fig. **3**) indicating a very good fit of model [19]. Further, areas under ROC curves for CC, ND, RC, CS, and KG are 0.813, 0.825, 0.785, 0.719, and 0.72 respectively.

4.1.3. Cross Validation of the Logit Model

Cross-validation is the process of assessing how the results of a statistical analysis will generalize to an independent data set. Two fold cross-validation method is used in this research: it assigns data points to two sets d and d_1 so that both sets are of equal size (this is usually implemented by shuffling the data array and then splitting it in two). The method then involves training (compute coefficients) on d and testing (the ability of the resulting model to predict) on d_1, followed by training on d_1 and testing on d. In this study training and test sets are both large, and each data point is used

for both training and validation.

(a) Cross Validation for Total Data (500 entries)

Both d and d_1 have 250 data entries each. These are obtained by randomly picking these data entries. Firstly, d is considered as given dataset of known data on which training is run (training dataset). The model is developed on data set d and tested against the testing data set. The logit equation is given by equation (9) and the results of model validation using classification table are presented in Table **6**.
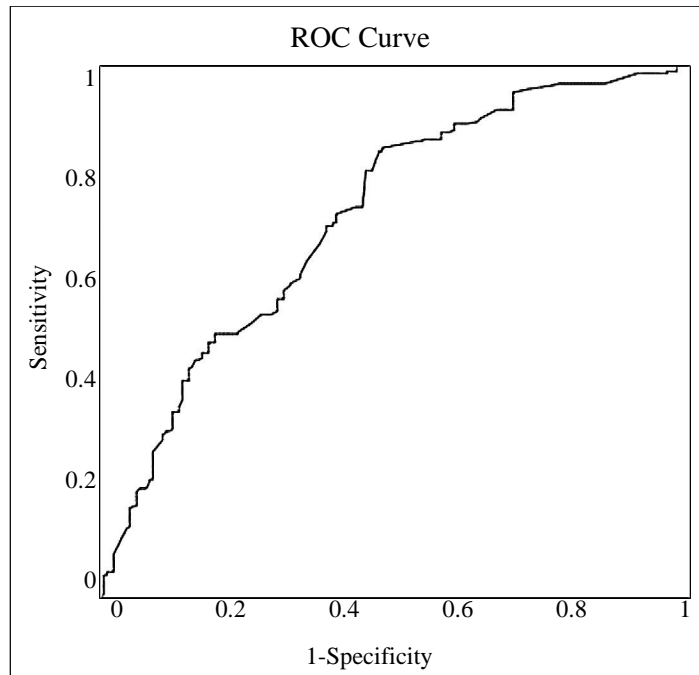
Fig. (3). Receiver operating characteristic (ROC) curve.

Table 6. Validation of d data entries using the logit model.

Observed		TRAINING SET(250)			TESTING SET(250)			
		Predicted(Based on d)			Predicted(Based on d_1)			
		Mode		%	Mode		%	
		0	1	Correct	0	1	Correct	
Mode	0	34	56	37.8	46	44	51.1	specificity
	1	20	140	87.5	33	127	79.4	sensitivity
Overall %				69.6			69.2	

$$L = ln\ (odds) = ln\ (p/1\text{-}p) = 1.766 + .657X_1 + 1.087X_2 - .037X_3 - .011X_4 - .032X_5 \tag{9}$$

As shown in Table **6** the testing results have an accuracy of 69.2% in data set d_1 which is fairly acceptable. Next, both the data sets are interchanged. Based on the variables, the logit Equation (10) is derived. The model is validated using a similar classification table. The accuracy of prediction is found to be 68.9% and 68.4% for the training and testing data set respectively, again well within the acceptable region [19].

$$L = ln\ (odds) = ln\ (p/1\text{-}p) = .700 + .571X_1 + 1.668X_2 + .062X_3 - .007X_4 - .016X_5 \tag{10}$$

(b) Cross Validation for individual stations (100 entries each)

Cross validation of the model using the entire data set provided convincing evidence of the validity of the model. However to still probe further and strengthen the evidence of the predicting ability of logistic regression, cross-validation for data from each station has also been performed. Two data sets of 50 data entries each from every station

are used. Then cross validation is performed as detailed earlier. The results again demonstrate the validity of the model even for individual stations and are presented in Table **7**.

Table 7. Cross validation output for all five data sets.

DATA SET	Observed		TRAINING SET (50)			TESTING SET (50)		
			Predicted					
			Mode		% correct	Mode		% Correct
			0	**1**		**0**	**1**	
KG	Mode	0	16	9	64.0	10	6	62.5
		1	13	12	48.0	14	20	58.8
	Overall percentage				56.0			60
CC	Mode	0	4	8	33.3	13	5	72.2
		1	1	37	97.4	6	26	81.3
	Overall percentage				82.0			78
ND	Mode	0	16	3	84.2	35	4	89.4
		1	11	20	64.5	4	7	63.7
	Overall percentage				72.0			84
RC	Mode	0	12	7	63.2	29	8	78.4
		1	8	23	74.2	5	8	61.5
	Overall percentage				70.0			74
CS	Mode	0	4	16	20.0	14	7	66.7
		1	8	22	73.3	8	21	72.4
	Overall percentage				52.0			70

4.2. Vehicle Ownership Split Model

To gain further insights into the mode shift, the effect of 2Ws and cars individually on the shift to metro is also studied. For this study, two additional categorical explanatory variables are defined to explain vehicle ownership (*i.e.*, car and 2-Ws). The details of explanatory variables now are as follows:

Quantitative Variables

Ingress distance to Metro (Km) X_1

Age (Years) X_2

Income (in thousands per month) X_3

Categorical Variables

Gender (Male/Female) X_4

(Coded as 1 for Female and 0 for Male)

Car Ownership (Yes/No) X_5

(Coded as 1 for Yes and 0 for No)

Two-Wheeler (2W) Ownership (Yes/No) X_6

(Coded as 1 for Yes and 0 for No)

Standard Logistic Regression is performed using SPSS and the results are summarized in Table **8**.

Table 8. Results (with mode split).

	B	**S.E.**	**Wald**	**Df**	**Sig.**	**Exp(B)**
Access	0.024	0.038	0.386	1	0.534	1.024
Age	-0.011	0.011	0.976	1	0.323	0.989
Income	-0.006	0.008	0.58	1	0.446	0.994
gender(1)	0.635	0.334	3.621	1	0.057	1.888
car(1)	-2.012	0.291	47.644	1	0	0.134

(Table :) contd.....

	B	S.E.	Wald	Df	Sig.	Exp(B)
2Ws(1)	-0.561	0.279	4.049	1	0.044	0.571
Constant	1.903	0.414	21.116	1	0	6.707

$$L = ln\ (p/1\text{-}p) = 1.903 + .024X_1 - 0.011X_2 - 0.006X_3 + 0.635X_4 - 2.012X_5 - 0.561\ X_6 \qquad (11)$$

As shown in Table **8**, three variables viz., gender, car ownership and 2W ownership are significant. The females are almost twice (1.888) more likely to have shifted from buses to metro than the male counterparts (Exp(B) for gender (1) = 1.888). Commuters not owning a car are 7.4 times (1/.134) more likely to shift to the metro from buses than commuters owning a car (Exp(B) for car (1) = 0.134). Similarly, commuters not owning a motorcycle are 1.75 times more likely to shift to the metro than commuters owning a motorcycle (Exp(B) for 2Ws (1) = .571).

Further, the analysis is also carried out for each station separately and the findings of the model above are reinforced. The detailed results are presented in Table **9** and the highlights are as follows:

Table 9. Variables in the equations station wise (split).

	KG 01-100		CC 101-200		ND 201-300		RC 301-400		CS 401-500	
	B	Exp(B)	B	Exp(B)	B	Exp(B)	B	Exp(B)	B	Exp(B)
Access	.179	1.196	.069	1.071	-.961	.383	-.490	.613	.052	1.053
Age	.010	1.010	-.037	.964	-2.667	.069	-2.506	.082	-.008	.992
Income	.020	1.021	-.039	.962	19.098	1.96×10^8	1.760	5.813	-.033	.968
Gender	-.160	.852	1.865	6.453	-.005	.995	-.003	.997	.511	1.666
Car	-1.713	.180	-1.724	.178	-.031	.969	.000	1.000	-1.155	.315
2Ws	-.150	.861	-.204	.815	-.036	.964	.053	1.054	-.282	.754
Constant	-.208	.812	3.665	39.066	2.945	19.005	1.829	6.229	2.070	7.929

- The females are generally more likely to have shifted from buses to metro than the male counterparts. The same is strongly evident from the analysis of CC and CS data (value of Exp(B) for gender are 6.45 and 1.67).
- Commuters not owning a car are more likely to shift to the metro from buses than commuters owning a car. Commuters not owning a 2W are more likely to shift to the metro from buses than commuters owning a 2W. Further, motorcycle owners are more likely to shift into metro from buses than the car owners (value of Exp(B) for car and 2Ws).

5. DISCUSSIONS

Several studies [7, 20 - 24] establish an urgent need to improve the quality of public transport, particularly in terms of comfort, directness, punctuality, travel time, and integration of different modes to reduce the increasing reliance of commuters on PMVs. Studies also reveal that commuters can actually shift to public transport if their concerns are addressed. Tiwari and Jain [25] conclude that commuters can easily travel by bicycles up to a distance of 10 km. Suman *et al.* [26] reveal that 25% of non-bus users are willing to use bicycles for daily commute if separate lane is reserved for them. Further, 52% bus users can potentially shift to bicycles and consequently free up space inside buses thus increase comfort and enhancing bus attractiveness to non-bus users. Furthermore, Suman *et al.* [26] also reveal that if a common ticketing system for buses and Delhi metro is available, 36% non-bus users are willing to shift to buses. Additionally, 64% experts believe that implementing common ticketing system is feasible in Delhi. More studies [20, 22, 24] share similar findings and conclude such integrated ticketing systems can improve public transport, a prime need of the current *era*.

Delhi metro is an attempt to provide quality public transport that is comfortable, quick and safer. Commuters using both PMVs and buses (the existing major mode of public transport) have shifted to the metro for their commuting needs. This paper, as discussed in section 1, analyses the relative mode shifts. The findings suggest that a bulk of the metro users, 57% to be precise, have shifted from buses and only 28.8% from PMVs. Further, commuters not owning car(s) are 7.4 times more likely to shift to the metro than those owning one (or more). Thus, while many bus commuters find the quality of the metro better (hence the shift), commuters using PMVs are less enthusiastic using shifting to

metro. This clearly points to two phenomenon and corresponding policy measures:

- The quality of public transport matters. Commuters shift from one mode of public transport to another in search of better quality (bus to metro). A shift from PMVs to a good quality public transport mode (PMV to metro) is also possible. So, all modes of public transport should strive to improve their quality and commuters will respond commensurately. Specifically, busses in Delhi need to improve their service quality attributes significantly to retain their ridership. They are the most cost effective mode of urban transport [27] and are crucial to the success of the public transport strategy of Delhi.
- Improving the quality of public transport alone is not sufficient to affect the desirable mode shift from PMV to public transport (metro in this case). In this study, this is reflected in the low share of PMV to metro and the low likelihoods of commuters owning PMVs shifting to the metro. Therefore, strategies to incentivize the use of public transport, in addition to improved quality of public transport, should include measures to dis-incentivize PMVs. An example of such a measure is congestion charging. Although initially likely to be contested by citizens, these measures can become popular once the benefits are apparent.

Similarly, those who do not own 2W(s) are 1.75 times more likely to shift to metro than those owning one (or more). For example, in 2005, 55% residents of Stockholm were not satisfied with implementation of congestion charging but later accepted it and appreciated the positive effect in reducing travel time and PMVs use [28, 29].

CONCLUSION

Mode shift from buses to metro occurs because buses take more time, and are more crowded compared to the metro. Further, commuters prefer direct mode of transport that is possible for many of them who shifted to the metro. In addition to this shift, some commuters also shift from PMVs to the metro because it is cheaper and less time consuming as compared to PMVs. The analysis also reveals, as expected, the females perceive the metro to be safer and are more likely to shift as compared to males. The possible drivers for this are CCTV camera availability, security personnel on stations, more space inside as compared to buses even when crowded, and separate coaches for females.

It is important to note, however, that despite, introduction of a good metro system in Delhi, the mode share of public transport is continuously decreasing. Also, majority of the metro commuters have shifted from buses and new addition to the public transport domain is not considerable. Therefore, as presented in the discussion section, improvement in various service attributes is necessary along with dis-incentivising PMVs to enhance the overall mode share of public transport. Possible measures to achieve this include: 1) improved comfort, punctuality, and travel time through addition of more buses, along with optimal route allocation of existing ones and implementation of common ticketing system for buses and the Delhi metro, 2) separate lanes for bicycles, and 3) betterment of dis-incentivization of PMV's through measures such as congestion charging.

Future Scope

This study alone is not sufficient to formulate detailed guidelines for transportation in Delhi. The limitation of this study include response only from metro users and lack of a detailed analysis of the perception of commuting by metro. To overcome these limitations and gain more insights, such a study can be carried out on buses as well. The study should include a detailed perception analysis of existing and potential bus commuters. An analysis of the impact of various interventions by the metro and buses to increase their ridership will further extend and enhance the findings of this study.

CONFLICT OF INTEREST

The authors confirm that this article content has no conflict of interest.

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