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ANALYSIS OF VEHICLE OWNERSHIP ATTRIBUTES IN WESTERN PROVINCE, SRI LANKA

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ABSTRACT

This paper develops a mathematical model to predict motor vehicle ownership based on household (HH) characteristics. The model is tested using household visit surveys in the Western Province of Sri Lanka (CoMTrans, 2014). The province which has the country's highest population density (1,600/km²) and road density (0.9 km/km²) as well as a motor vehicle ownership of 206 vehicles per 1,000 people. The modelling is disaggregated into motorcycles, three-wheelers, vans, and cars (including jeeps and pick-ups). The motor vehicle fleet comprises 51% motorcycles, 20.2% three-wheelers, 6.7% vans, and 17.7% cars apart from commercial vehicles. The purchasing cost of motor vehicles in Sri Lanka varies widely due to different taxes imposed at importation.

A binary logistic regression with cross-validation statistical theories was used to predict the HH ownership of different vehicles, based on an income-based testing scenario for determining a HH's likelihood of owning a particular type of vehicle. Motorcycles, three-wheelers, vans, and cars listed in ascending order of cost of ownership and operation were tested against the characteristics of 35,850 HHs using R, a software analytical tool. The analysis found that private vehicle ownership depends on attributes of a HH, such as its size, average monthly income, and the percentage of workers, school and kindergarten children, and males in that HH.

Keywords: *Vehicle Ownership, Household Characteristics, Regression Analysis, Western Province, Household Visit Survey*

1. INTRODUCTION

Vehicle ownership affects the ability of road transport infrastructure capacity in a country to cope with traffic congestion and delays; particularly when demand exceeds the road space supply. Vehicle ownership depends on several factors, including HH income, HH size, HH composition, gender, and social status [1],[2]**.** Increased income makes vehicles more affordable to own and operate, and the rate of multiple vehicle ownership also increases. Ingram and Liu (1999) having tested income elasticity of car ownership for fifty countries found that it ranges from 1.02 to 1.21, indicating that for every 10% increase in income, car ownership increased by 12% [3]. David Bannister (2006) observes that the car has become "an icon of the twentieth century" and Urry (2001) states that the car has become a "symbol of social status" [4][3]. When the quality, including the reliability and comfort of public transport, slackens, and private vehicle ownership increases, people become reluctant to use public transport.

Western Province, the central administrative and commercialized province in Sri Lanka consists of three districts: Colombo, Gampaha, and Kalutara. It has a land area of 3,684 km^2 wherein 28.73% population of Sri Lanka resides. The population sample used for the analysis consists of 35,850 HHs made up of 124,673 individuals. This data was collected by a CoMTrans (urban transport system development project for Colombo Metropolitan Region and Suburbs) study from 2013 to 2014, and classified HH income into three groups, as shown in Table 1.1.

Table 1.1 Summary of Income by Group

Group	Income Range	Mean Household Income	Percentage of Households
A	More than LKR 80,000	LKR 186,164	5%
B	LKR 40,000- 80,000	LKR 56,810	19%
C	Less than LKR40,000	LKR 24,009	76%

Note: 1 USD = approx. 127 LKR in 2013

2. LITERATURE REVIEW

The decision to own a private vehicle and the type of vehicle depends on different HH characteristics, such as its income, size, the number of license holders, composition in full-time workers and children, education level, gender and age[1],[2]. Ha, et al. (2019), using important variable ranking methods as Multi-nominal Logit model, Neural Networks and Random Forests, found that income is the most potent variable influence on motorisation among other HH characteristics [5]**.** Schievelbein et al. (2016) surveyed India to predict the type of vehicle, including motorised two wheels and four wheels that a HH will own by using a Multi-Nominal Logit model (MNL). It was found that the likelihood of four-wheel vehicle ownership increases with income and the HH size [6]. In some cases, it was evident that the strong influence of HH income on HH car ownership had diminished quite remarkably and the effect of HH size had increased significantly. However, Ritter et al. (2013) have found that even though HH size declined in Germany, the number of cars on German roads increased moderately, at about 0.2% per annum: a trend that will continue until 2030 [7]. Maltha, Y. (2016) found that the HH income was the most influential factor in vehicle ownership together with HH size, gender, age, education, suburbanisation, and working status in the Netherlands between 1987 and 2014 [2].

Moreover, it was found that high-income HHs tend to own luxury vehicles rather than own more vehicles [2]. In Phnom Penh in 2019, Ha et al. has applied the MNL, neural networks, and random forest and found that the presence of children in a HH appears to be another factor that determines the type of vehicles and results in a higher level of mobility, convenience and safety [5]. Kim et al. has used MNL and found that HHs in the United States commonly choose vans when they have more children under 8, or have older primary drivers [8].

3. RESEARCH METHODOLOGY

This study examines the vehicle ownership pattern in the Western Province of Sri Lanka with a comprehensive set of socio-economic characteristics of HHs observed in the Home Visit Survey (HVS). It was conducted by CoMTrans from 2013 to 2014 to prepare a comprehensive long-term transportation plan for Western Province. After removing HHs with missing values for any of the variables used, the sample consisted of 35,850 HHs. The availability of the motor vehicle in a HH was used as the dependent variable in the modelling. The following independent variables were selected to test their influence on HH vehicle ownership.

(i) Household income

(ii) Household size,

(iii) Household composition
   a. Percentage of workers in a household
   b. Percentage of school and kindergarten children in a household (i.e., children > 5years)
   c. Percentage of males in a household

Vehicles in the HH survey were categorised into three basic categories including as 2W (motorcycle), 3W (three wheels) and 4W (car, jeep and pickup) with Vans as a subcategory. This data has been analysed descriptively using MS Excel and modelled mathematically using the R software. Six different scenarios of motor vehicle ownership in a HH were examined using the logistic regression technique as follows:

- **Case 1:** Households having any motor vehicle: Households with any vehicle are assigned "Yes" with all other households assigned "No".
- **Case 2:** Households having just one 2W or 3W vehicle: Households owning just one 2W or 3W are assigned "Yes" while all other households are assigned "No".
- **Case 3:** Households having more than one 2W or 3W: Households owning more than one 2W or 3W but not having 4W and van are assigned "Yes" and all other households assigned "No".
- **Case 4:** Households having just one van irrespective of any 2W or 3W but not having a 4W vehicle: These are households owning just one van irrespective of the number of less expensive vehicles identified as 2W or 3W, but excluding those households owning more expensive 'non-van' 4Ws.
- **Case 5:** Households having just one 4W, irrespective of the number of 2W, 3W or vans: Households owning just one 4W irrespective of any 2W, 3W and vans are assigned as "Yes" and all other households assigned as "No".
- **Case 6:** Households having more than one 4W irrespective of the number of 2W, 3W or vans. In this case, households with more than one 4W irrespective of other vehicles were assigned "Yes" while all other households were assigned "No".

Models for each of these six scenarios were generated using binary logistics regression with cross-classification.

3.1 Logistics Regression Theory

Let, $P_i = \Pr(Y = 1 | X = x_i)$ ……………………………… (1)

which can be written as

$\text{Log}\,[P_i / (1- P_i)] = \text{logit}\,(P_i) = \beta_o + \beta_1 x_1 + \beta_2 x_2 + \ldots + \beta_i x_i$ ……… (2)

where, P_i is the probability of having a HH owning a particular type of vehicle, and x_i is the variables which affect the vehicle ownership. β_o, β_1 are parameters.

The probability of owning a vehicle is:

$$P_i = \exp \text{logit}\,(P_i) / [1 + \exp (\text{logit}\,(P_i)] \quad \ldots\ldots\ldots\ldots (3)$$

Conversely, the probability of not owning that particular vehicle type is

$$1 - P_i = 1/ [1 + \exp (\text{logit}\,(P_i)] \quad \ldots\ldots\ldots\ldots\ldots (4)$$[9]

In the regression, the total sample of 35,850 HHs were divided into two groups as a training data set and the testing data set in keeping with the 80:20 rule. The predicted models were generated using the training data set comprising 28,704 HHs and validated with the balance 7,146 HHs. The models, therefore, give the probability (P) of “Yes” relative to “No”.

$$PV \begin{cases} 1, & P > 0.5 \\ 0, & P <= 0.5 \end{cases}$$

If the probability is more than 0.5, the predicted value (PV) will be rounded as “1” and if otherwise as “0”. Misclassification error and accuracy of the model are calculated using the confusion matrix.

4. ANALYSIS

The analysis is organized into two sections. Section A includes the descriptive analysis of variables assumed to be correlated with owning a motor vehicle (yes or no) and Section B, which includes the models calibrated using binary logistics regression.

4.1. Section A: analysis of vehicle ownership from HVS data

In the Household Visit Survey (HVS), the study team collected the previous day’s travel activity information of each of the residents from each of 38,500 HHs in the survey sample along with the socio-economic information of that HH and its occupants over the age of 5 through a structured interview survey. This survey also documented vehicle ownership of the HH by type of vehicle.

The sample's socio-economic profile shows that 36% of all individuals in these HHs are employees, while 23% are classified as school, kindergarten, and tertiary students. The remaining 41% is made up of the unemployed, retired, housewives, and others. It is also noted that 21% of HH members are below 18 years and that 64% are between 18 and 60 years.

The distribution of the data on (a) HH size, (b) the number of workers in a HH, (c) number of students in the HH, and (d) the number of males in the HH as shown in Figure 4.1 were tested with the Anderson-Darling test to check the normality in the distribution of the data set. The resulting P values were found to be less than 0.05, showing that the histograms are right-skewed distributed.

Since the variables are not normally distributed, the Wilcoxon rank test was used for continuity correction, confirming a significant relationship between vehicle ownership and the four socio-economic variables discussed.

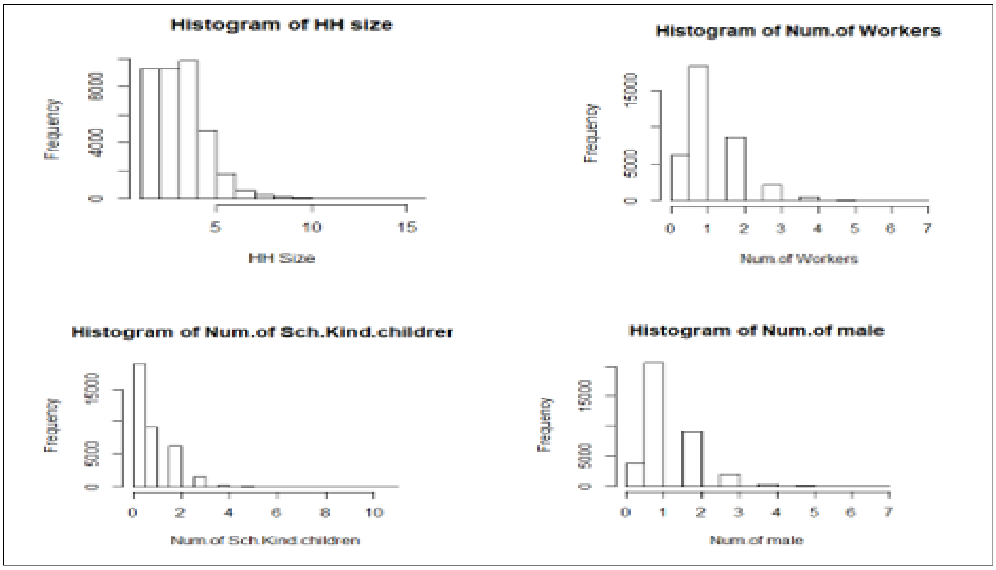

Figure 4.1: Histograms of Socioeconomic Data

The vehicle ownership in the different HHs categorized as being in Income Group A, B or C where A: High income = HH monthly income being more than Rs. 80,000, B: Middle income = HH monthly income being between Rs. 40,000, and Rs. 80,000 and C: Low income = HH monthly income being less than Rs. 40,000 was tested and found to be significant using the Chi-Square test as it resulted in a P value less than 0.05. Therefore, it can be concluded that there is a significant association between the HH income and the decision to own a vehicle.

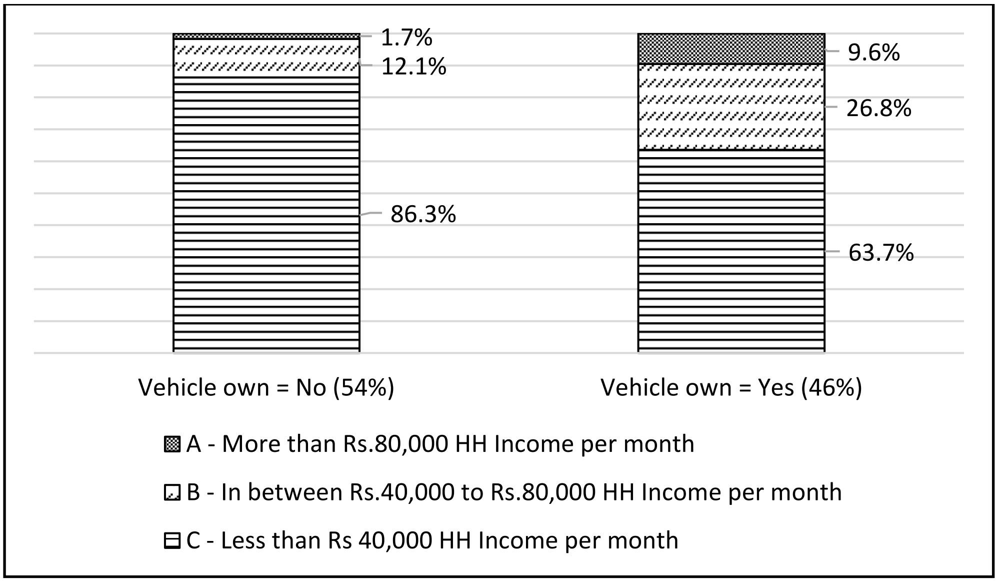

Figure 4.2: Distribution of HH vehicle ownership with HH income

When considering the residual analysis of income groups, HH income contributes to vehicle ownership on HHS in Income Group A and B more than Income Group C. Figure 4.2 above shows income to be an influential factor in deciding to own a vehicle.

The analysis shows that approximately 46% of HHs in the province own a vehicle. Out of the total vehicle owning HHs, 20% of HHs own more than one vehicle. Figure 4.3 shows the percentage of HHs relative to the number of HH members for the number of vehicle ownership separately.

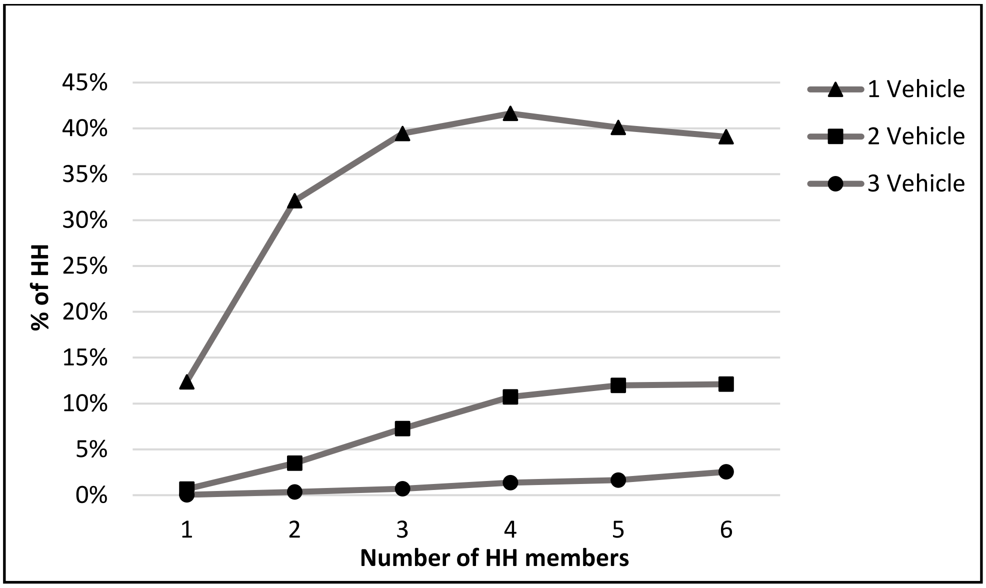

Figure 4.3: Variation in the Number of Vehicles Owned by a HH by the Number of HH members

This reveals that most HHs own only one vehicle even though they have five or six members. However, the percentage of HHs owning one vehicle decreases when there are four or more HH members; the percentage of HHs owning two or more vehicles increases with the number of HH members.

Figure 4.4 shows the vehicle ownership of a HH when compared with the Income Groups. It is seen that most of the low and middle-income HHs (Group B and C respectively) have more than two 2W or 3W vehicles. Most low-income HHs (Group C) have 2W and 3W, and middle income HHs (Group B) have 2W and 4W. Since the capital and operating cost increases from 2W to 3W to van to 4W, most low and middle-income HHs tend to own 2W or 3W, while the high-income HHs own 4Ws. Consequently, it appears that middle and low income HHs use vans for commercial purposes and 2W for personal use.

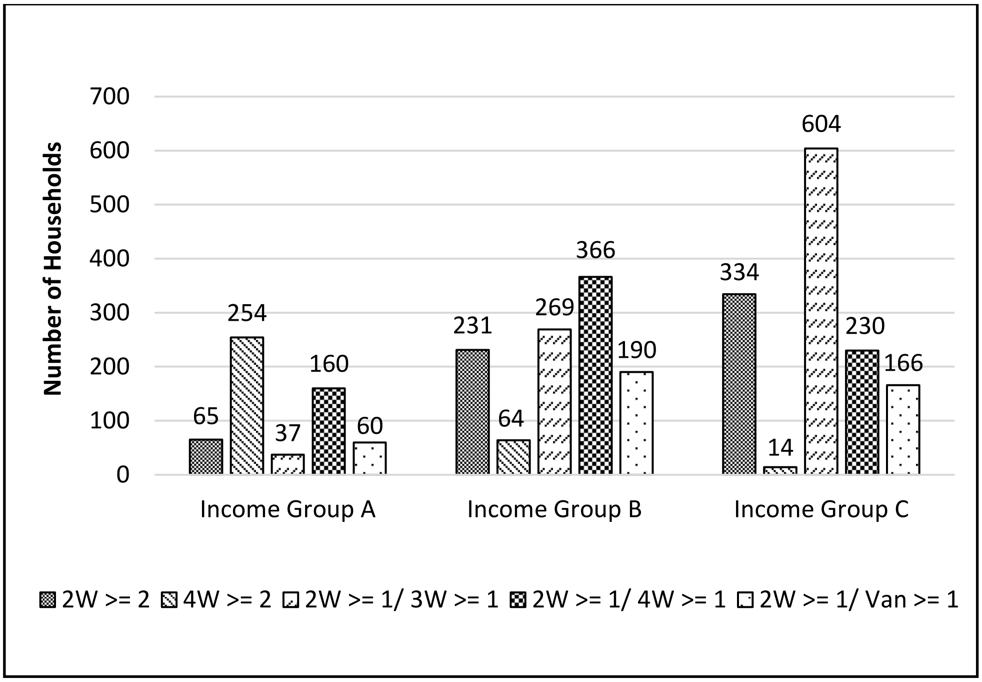

Figure 4.4: Vehicle Composition with Different Income Groups

Figure 4.5 shows the type of vehicle owned by HHs in each income group. Most of the low-income HHs in Group C own a 2W or 3W while most high-income HHs in Group A own a 4W and most middle-income HHs (Group B) own 2Ws. Even though the capital and operating cost of 3W is higher than a 2W, most of the low-income HHs own a 3W.

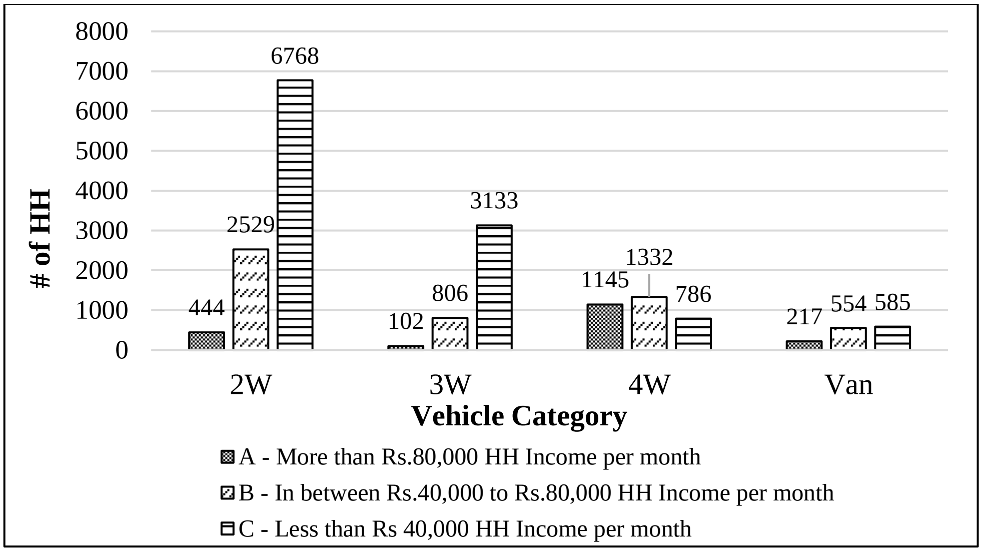

Figure 4.5: Distribution of Vehicle Category by HH Income Group

Table 4.1: Vehicle Ownership with Household Composition

	4W ownership	2W ownership
% of workers in HH < 50%	8%	25%
% of workers in HH >= 50%	11%	31%
% of sch/kind. members in HH <50%	9% (8.98%)	27%
% of sch/kind. members in HH >= 50%	9% (9.22%)	28%

Table 4.1 shows the variation between the number of workers and the number of school children relative to HH vehicle ownership. It shows that parents tend to own either a 4W or a 2W when they have school children. However, this does not influence the vehicle ownership as much as the percentage of workers in a HH does. It can also be seen that the percentage of workers in a HH has a greater influence on 2W ownership than 4W ownership.

4.2. Section B: Prediction Models for Different Types and Number of Vehicles

Table 4.2 A: Binary Logistics Regression results- Case 1

Case 1: Households having any vehicle				
	Estimate	Std. error	Z value	P-value
Intercept	0.0944472	0.0791376	1.193	0.233
HH size	0.1581206	0.0097131	16.279	<2e-16***
Household Income Group B	-0.8904475	0.0707832	-12.580	<2e-16***
Household Income Group C	-1.8584546	0.0666605	-27.879	<2e-16***
% of workers in a HH	0.0070714	0.0005159	13.707	<2e-16***
% of sch. &kind. students in a HH	0.0067407	0.0006492	10.384	<2e-16***
% of males in HH	0.0120167	0.0005961	20.157	<2e-16***
Accuracy	62.82%			
95% CI	0.6169, 0.6394			
Sensitivity	71.70%			
Specificity	52.10%			

*Note: ***, **, * refer to p-value at the three ranks of less than 0.001, 0.01 and 0.05, respectively.*

Table 4.2 B: Binary Logistics Regression results- Case 2

Case 2: Households having just one 2W or 3W				
	Estimate	Std. error	Z value	P-value
Intercept	-2.9145060	0.0728893	-39.98	<2e-16***
HH size	0.1657130	0.0083243	19.91	<2e-16***
Household Income Group B	1.2653976	0.0612229	20.67	<2e-16***
Household Income Group C	1.4087321	0.0584063	24.12	<2e-16***
% of workers in HH	0.0092014	0.0004586	20.06	<2e-16***
% of sch. &kind. students in a HH	0.0070525	0.0005547	12.71	<2e-16***
% of males in HH	0.0111966	0.0005347	20.94	<2e-16***
Accuracy	56.24%			
95% CI	0.5508, 0.5740			
Sensitivity	51.99%			
Specificity	66.75%			

*Note: ***, **, * refer to p-value at the three ranks of less than 0.001, 0.01 and 0.05, respectively.*

Table 4.2 C: Binary Logistics Regression results- Case 3

Case 3: Households having more than one 2W or 3W only				
	Estimate	Std. error	Z value	P-value
Intercept	-3.5334597	0.0645403	-54.748	<2e-16***
HH size	0.4936797	0.0078771	62.673	<2e-16***
Household Income Group B	0.8213394	0.0455818	18.019	<2e-16***
Household Income Group C	0.4941094	0.0436329	11.324	<2e-16***
% of workers in HH	0.0147712	0.0004556	32.422	<2e-16***
% of sch. &kind. students in a HH	-0.0031693	0.0005083	-6.236	4.5e-10***
% of males in HH	0.0112119	0.0005424	20.670	<2e-16***
Accuracy	65.31%			
95% CI	0.6419, 0.6641			
Sensitivity	65.32%			
Specificity	65.02%			

*Note: ***, **, * refer to p-value at the three ranks of less than 0.001, 0.01 and 0.05, respectively.*

Table 4.2 D: Binary Logistics Regression results- Case 4

Case 4: Households having just one van irrespective of 2W and 3W but no 4Wvehicles				
	Estimate	Std. error	Z value	P-value
Intercept	0.2673233	0.0500656	5.339	9.32e-08 ***
HH size	0.0651332	0.0075617	8.614	<2e-16 ***
Household Income Group B	-0.0438927	0.0364731	-1.203	0.229 ***
Household Income Group C	-1.4450727	0.0347124	-41.630	< 2e-16 ***
% of workers in HH	-0.0038323	0.0004023	-9.525	< 2e-16 ***
% of sch. &kind. students in a HH	0.0040626	0.0004977	8.162	3.29e-16 ***
% of males in HH	0.0098639	0.0004838	20.390	< 2e-16 ***
Accuracy	75.24 %			
95% CI	0.7423, 0.7624			
Sensitivity	76.14%			
Specificity	50.20%			

*Note: ***, **, * refer to p-value at the three ranks of less than 0.001, 0.01 and 0.05, respectively.*

Table 4.2 E: Binary Logistics Regression results- Case 5

Case 5: Households having just one 4W, irrespective of the number of 2W, 3W and vans				
	Estimate	Std. error	Z value	P-value
Intercept	3.0093457	0.0556340	54.092	< 2e-16 ***
HH size	-0.1695371	0.0088840	-19.083	< 2e-16 ***
Household Income Group B	-1.3272376	0.0408924	-32.457	< 2e-16 ***
Household Income Group C	-3.5429937	0.0403872	-87.726	< 2e-16 ***
% of workers in HH	-0.0081569	0.0004427	-18.427	< 2e-16 ***
% of sch. &kind. students in a HH	0.0025536	0.0005709	4.473	7.71e-06 ***
% of males in HH	0.0044182	0.0005148	8.582	< 2e-16 ***
Accuracy	79.71%			
95% CI	0.7876, 0.8064			
Sensitivity	80.27%			
Specificity	73.37%			

*Note: ***, **, * refer to p-value at the three ranks of less than 0.001, 0.01 and 0.05, respectively.*

Table 4.2 F: Binary Logistics Regression Results- Case 6

Case 6: Households having more than one 4W irrespective of the number of 2W, 3W and vans				
Intercept	3.0856231	0.0591624	52.155	< 2e-16 ***
HH size	-0.0635705	0.0112819	-5.635	1.75e-08 ***
Household Income Group B	-2.8347234	0.0349123	-81.196	< 2e-16 ***
Household Income Group C	-5.6656974	0.0414249	-136.770	< 2e-16 ***
% of sch. &kind. students in a HH	-0.0136984	0.0007322	-18.709	< 2e-16 ***
% of males in HH	0.0148247	0.0022622	6.553	5.63e-11 ***
Accuracy	85.81%			
95% CI	0.8498, 0.8661			
Sensitivity	85.77%			
Specificity	88.60%			

*Note: ***, **, * refer to p-value at the three ranks of less than 0.001, 0.01 and 0.05, respectively.*

Vehicle ownership prediction models were developed for the six different cases identified earlier using Binary Logistics Regression. Table 4.2 shows the results and accuracy of each of these six models. It is seen that most of the coefficients are statistically significant, except the percentage of workers in HHs, which is not significant in Case 6.

This sample appears to predict better the ownership of 4W vehicles than the ownership of 2W, 3W and Vans. The highest sensitivity that explains the probability of accurately predicting a HH owning more than one 4W is the highest at 85.77% which also gives the highest specificity of 88.60% being the probability of accurately predicting a HH not owning more than one 4W.

In the model for Case 1, the HH size is the most influential factor in ownership of any motor vehicle. Simultaneously, the percentage of males in a HH is seen to have a higher impact than the percentage of school/kindergarten students and workers. Based on the Case 2 results, it is seen that mostly the middle and low-income HHs demonstrate 2W or 3W ownership. Moreover, HH size and percentage of males in a HH appear to have a more positive impact than the percentage of school/kindergarten and workers in a HH when a HH owns just one 2W or 3W vehicle. Also, HHs with more members and more male members and HH workers tend to own more than one 2W and 3W (Case 3). Middle income HH has a high possibility of owning more than one 2W or 3W than low-income HH.

The prediction model for Case 4 shows that HHs having a van instead of a car has a positive coefficient for HH size, number of school/kindergarten students and males in a HH. Furthermore, the HH size has the largest positive coefficient influencing van ownership, together with the percentage of males in a HH.

The intercept and coefficient for the percentage of school/kindergarten students in a HH and the percentage of male members in a HH have a positive impact on just one 4W in the predicted model for Case 5. However, low income has a more negative impact on 4W ownership than van ownership. Percentage of HH workers does not affect predicting more than one 4W ownership (Case 6). Middle and low-income HHs have a more negative impact on the ownership of more than one 4W than all other cases.

5. DISCUSSION OF RESULTS

Binary Logistics Regression is developed in this study for six different scenarios to investigate the effect of five different socioeconomics factors on the ownership of different vehicles in a HH ranging from the least to the most expensive vehicle category in Sri Lanka. Findings of this study provide further evidence on the contribution of different socio-economic factors on the ownership of each vehicle type.

5.1 Household Monthly Income

The middle and low-income HHs demonstrate a positive impact on 2W and 3W ownership, while high income HHs show a greater likelihood of 4W vehicle ownership. Results confirm that HH income has a positive effect on both the number of vehicles and the type of vehicle that a HH owns. This confirms Ha et al's finding that income is the most potent variable influencing motorisation, among other attributes[5]. This means vehicle ownership is most affected by HH income.

5.2 Number of Members in a Household

The result shows that the number of members in a HH has a positive impact on 2W, 3W and vans ownership. It also means that HHs with more members prefer to own a van than a car. The number of members in a HH is also observed to have a positive impact on both the type of vehicle and the number of vehicles.

5.3 Percentage of Males in a Household

It is found that the ownership of motor vehicles in a HH increases when the percentage of males increases. By comparison of coefficients, this was found to be most significant in the case of the ownership of 2W and 3W vehicles and vans.

5.4 Percentage of School/Kindergarten Students in Household

Based on the Case 2 results, it is seen that middle income HHs mostly own a 2W or 3W. It was found that owning a van is influenced by the number of school and kindergarten students. This compares well with Kim et al., who found that in the USA, that HHs having more children aged under eight commonly choose vans [8]. However, in some countries like Japan, HHs are more concerned about vehicle quality and ability to meet their requirements of mobility, convenience, and safety rather than the HH composition and economic level (Ha et al. (2019) [5].

5.6 Percentage of Workers in a Household

Results show that the percentage of workers in a HH has less influence on 4W vehicle ownership than 2W vehicle ownership. HHs tend to have more than one 2W when there have more workers. Kim et al. have also found that the number of workers is associated with a negative coefficient on minivans, midsized, or large sedans called family cars[8].

6. FUTURE RESEARCH

This research has some missing variables when compared to other models used for predicting vehicle ownership of a HH such as the demand to public transportation [10], the number of drivers, age of drivers in a HH [10], perception of the quality of public transportation services [5]and land use attributes [2], [11]. These variables can be used in future research to improve the accuracy of the model.

7. CONCLUSION

This paper can be viewed as an initial attempt to study the impact of HH's socio-economic attributes and composition on their vehicle ownership in Western Province, Sri Lanka. HVS data collected in 2013 was used to analyse the variation in vehicle ownership between different HHs attributes.

The monthly income, number of members, number of males and number of workers in a HH, show significant impact on vehicle ownership. Six models have been calibrated to estimate the level of ownership of different types of vehicles. This model could be applied in different parts of Sri Lanka and countries with similar vehicle taxation regimes to estimate the demand for different types of vehicles based on different socio-economic characteristics.

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