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Examining the effects of transport policy on modal shift from private car to public bus

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Abstract

Private vehicles have become the most common mode of daily travel. This is one effect of the poor accessibility of public transportation. This paper attempts to use a study based on a survey of commuters in order to devise ways of encouraging the use of public transportation. Two different public transport policies were examined: (i) once-an-hour direct bus service from home to university (policy 1), and (ii) park-and-ride facilities (policy 2). Binary logistics models are proposed with the intention of comparing the utility of travel modes between private cars and public buses. These models are also used to identify the factors which have the potential to encourage car users to switch from travelling by cars to public buses. Explanatory factors considered in all three models include: occupation, trip length, travel time, trip frequency, gender, age and possession of a license. We began from the basic scenario by focusing on existing services without considering any new policy. The consequences of two new policies were then analysed in order to identify those factors which influence the choice of travel mode and which can predict the probability of behavioural change. All the proposed logistics models are evaluated using real-world data (with 4410 samples) from a survey carried out at the University of Wollongong (UOW), Australia. Stated preference (SP) questionnaires were used to collect relevant information on the choice of travel mode. Based on the proposed models, findings identify a hierarchy of importance of relevant factors which could assist decision makers to design and implement more successful future transport service(s).

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Keywords: Transport policy; binary logistics; mode choice model

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1. Introduction

University commuters have complex and unique characteristics of travel behaviour [1], but their behaviour is not well understood or represented yet in demand models even though they comprise a significant proportion of the travel demand in a city [2]. Understanding the travel behaviour of university commuters, and particularly their reliance on the private car for commuting, can help universities and other stakeholders work on improvements of policies, programs, and infrastructure in order to encourage them to use public transport [3]. This is critical because the use of private cars directly affects the level of congestion in adjacent streets and has impacts on the well-being of students and employees as well as surrounding neighbourhoods.

Research has been done on different aspects of the travel behaviour of university students. This includes visualising and evaluating travel behaviour using GIS [4], mode choices [5,6,7], and statistical and activity patterns [8,9,10]. Other investigations have focused on traffic safety attitudes and the driving behaviour of students [11], enjoyment of commuting on different modes of transportation [12], and the cycling culture of university students [13], as well as the commuter habits and potentials for modal change in university settings [3].

In this paper, we take the University of Wollongong (UOW) in New South Wales, Australia as an example in order to investigate the mode choice of commuters in a university setting. This study considered the possible impact of policy interventions in encouraging UOW staff and students (*'UOW commuters' hereafter*) to encourage the use of public buses. The policy interventions were: (i) once-an-hour direct bus service from home to university to home (policy 1), and (ii) park-and-ride facilities at the urban fringe which is closer to the shuttle bus stop (policy 2). Three binary logistics models are proposed with the intention of comparing the utility of travel modes between private vehicles and public buses. In the first model, we started from the basic scenario by focusing on existing services without considering any new policy. The consequences of two new policies were analysed in the second and third model, respectively, in order to identify factors which influence the choice of travel mode and predict the probability of behavioural change in bus ridership. The mode choice models were used to forecast the proportion of riders who will use the selected modes (car and bus in this paper) in response to changes in different variables such as travel time or provision of new policies and accordingly assessed the effectiveness of the possible policy interventions.

The remainder of this paper is organised as follows. In Section 2, we briefly describe the materials and models that are employed in this paper. Model validity and results are included in Section 3. In Section 4, the mode choice probability prediction is stated and the outcomes of modal shift analysis are presented. Finally, Section 5 is the conclusion.

2. Materials and methods

This section is divided into two parts. The first part describes the data set and the second part presents the model specifications that were used to investigate UOW commuters' mode choice patterns as well as modal shift.

2.1. UOW dataset

UOW undertakes transport surveys, generally every two years, to understand the current modes of transport to support the needs of UOW commuters by providing new transport initiatives and infrastructure planning. This dataset, collected in 2011, was used in this paper. The stated preference (SP) questions, which were considered as policy interventions in this study, were included in this survey to observe the responses about the choice of commuting mode whether private car or public bus. The respondents were asked to consider the policies described below on choosing their anticipated travel mode and this paper examines the changes in their travel behaviour to public bus.

Policy 1: Once-an-hour direct bus from a central location in the commuters' suburb, travelling directly to and from the campus (model 2), and

Policy 2: Park-and-ride (PnR) service that provided car parking facilities at an urban fringe location *around Wollongong where a shuttle bus service connects to the campus (model 3).*

The survey also included questions associated with trip modes (from suburb to UOW) such as travel time, parking location, trip distance, departure time etc., and with individual characteristics such as age, gender, occupation, having driving license etc. Bicycle and motorbike trips were excluded from this study since they only constitute 2.1% and 0.7% of total trips, respectively. Walking trips were also disregarded even though they constituted 7.2% of the total trips since students only walk to UOW if they live in university accommodation or in very close residences, and therefore they are less likely to shift to other modes. The final number of observations was 4410 (1758 males and 2652 females).

2.2. Model specification

The logit function is an important part of discrete choice and logistic regression [14, 15]. Logit models were implemented for logistic regression analysis because of their ability to represent complex aspects of travel decisions of individuals by incorporating important demographic and policy-sensitive explanatory variables. It does not assume linearity in the relationships between the independent and dependent variables, and does not require the variables to be normally distributed. The logistic regression estimates the probability that a certain event would occur based on the independent variables.

A discrete choice model is a mathematical function which predicts an individual's choice based on utility or relative attractiveness [16]. According to the aim of this study, the binary logit model is employed as an analytically convenient modelling method. Mathematically, for the *n*-th individual, let *i* and *j* be the two alternatives in the choice set of each individual:

$$U_{in} = V_{in} + \varepsilon_{in} \quad (1)$$
$$U_{jn} = V_{jn} + \varepsilon_{jn} \quad (2)$$

Where U_{in} is the true utility of the alternative *i* to the *n*-th individual
V_{in} is the deterministic or observable portion of the utility estimated by the analyst
ε_{in} is the error of the portion of the utility unknown to the analyst

$$V_{in} = f(X_i, S_n) \quad (3)$$

Where X_i is the portion of utility associated with the attributes of alternative *i,*
S_n is the portion of utility associated with characteristics of the *n*-th individual

The deterministic component of utility can be written as below for model 1:

$$V_{Public\ bus\ (PB)} = \beta_0 + \beta_{1\_PB}*occupation + \beta_{2\_PB}*trip\ length + \beta_{3\_PB}*travel\ time + \beta_{4\_PB}*trip\ rate + \beta_{5\_PB}*having\ license + \beta_{6\_PB}*gender + \beta_{7\_PB}*age\text{; and} \quad (4)$$

For model 2 and 3:

$$V_{Public\ bus\ (PB)} = \beta_0 + \beta_{1\_PB}*occupation + \beta_{2\_PB}*trip\ length + \beta_{3\_PB}*travel\ time + \beta_{4\_PB}*trip\ rate + \beta_{5\_car}*having\ license + \beta_{6\_PB}*gender + \beta_{7\_PB}*age + \beta_{8\_PB}*frequency\ of\ new\ service\ use + \beta_{9\_PB}*willingness\ to\ pay\ for\ new\ service \quad (5)$$

Where β_0 is the constant, $\beta_1, \beta_2, \beta_3, \beta_4, \beta_5, \beta_6, \beta_7, \beta_8$ *and* β_9 are the coefficients of variables.

The probability that the *n*-th individual chooses alternative *i* (P_{in}) as proposed by Ben-Akiva and Lerman [16] is as follows:

$$P_{in} = \frac{1}{1 + e^{-v_n}} = \frac{e^{v_{in}}}{e^{v_{in}} + e^{v_{jn}}} \quad (6)$$

The probability that an individual will choose the public bus can be written as

$$P_{PB} = \frac{e^{v_{in}}}{e^{v_{in}} + e^{v_{jn}}} = \frac{e^{v_{PB}}}{e^{v_{PB}} + e^{v_{car}}} = \frac{e^{\beta(X,S)PB}}{e^{\beta(X,S)_{PB}} + e^{\beta(X,S)_{car}}} \tag{7}$$

Where P_{PB} is the probability that the n-th individual uses or switches to the public bus.

A binary logit model for university commuter trips was developed for two alternatives, namely, public bus and private car, in order to compare the utility of these travel modes and identify the factors which would influence car users to move from traveling by car to choosing a public bus. In this model, the dependent variable was "1" if the commuters' travelled by public bus and "0" for car use. In the UOW travel survey, the variables which were determined as relevant included: occupation, trip length, travel time, trip rate/frequency, having a license, gender, occupation (student or staff) and age. In order to evaluate the policies and to understand the responses of travellers to the proposed transport service, two additional explanatory variables were integrated: frequency of new service use and willingness to pay for this service.

The coefficients are estimated by fitting the data to the model(s). The maximum likelihood estimation method is a commonly used fitting technique. This method involves choosing values for the coefficients to maximise the likelihood (or probability) that the model predicts the same choices made by the observed individuals. The method yields highly accurate estimates.

3. Results and discussions

3.1. Modelling of current mode choice (without integrating new policy)

Car and public bus (Model 1)

A summary of estimations using the binary logit model for commuting to UOW by car versus public bus is presented in Table 1. All the variables presented in the table have significant parameter estimates and logical signs.

Table 1. Estimation results using binary logistics models (model 1).

	B	S.E.	Sig.	Odds ratio	95% C.I.	
					Lower	Upper
Gender	0.381	.087	.000	1.464	1.235	1.735
Trip distance in km	-4.391	.152	.000	.012	.009	.017
Travel time in min	-7.559	.263	.000	1918.26	1145.24	3213.05
Trip rate per week	-1.129	.360	.002	3.094	1.528	6.264
Age	-0.083	.045	.067	.920	.842	1.006
Having license	1.729	.165	.000	5.634	4.074	7.791
Occupation (either student or staff)	1.436	.170	.000	4.205	3.014	5.868
Constant	-9.206	.469	.000	.000		
Summary of statistics						
-2LL				3498.033		
Model chi-square				86.581		
Cox and Snell's R^2				0.405		
Nagelkerke value				0.554		
Hosmer and Lemeshow Chi-square (8)				86.581		
Number of observations				4410		

The *Sig.* = 0.000 represents the significant contribution of the variable in the model prediction. Thus, trip distance, trip rate, travel time, having a license, gender and occupation are significant variables. The odds ratio can be used to interpret the prediction of probability of an event occurring based on a one unit change in an independent variable when all other independent variables are kept constant. For instance, females are 1.464 times more likely to use public bus for commuting to the university than males. According to the results, the estimated coefficients for gender came out positive, implying that females would be using public bus instead of driving car. The estimated coefficients for travel time and trip distance for public bus were negative, implying that an increase in travel time and trip distance for the public bus was likely to increase the probability of car users to continue choosing the car as the preferred mode of transport. In the other words, an increase in travel time is likely to increase resistance to switching from private car to public bus. The likelihood of shifting car users to public bus was likely if reductions in travel time could be achieved by introducing relevant policies. The individual's trip rate per week coefficient for the public bus is negative, so an increase in their trip rate would decrease their bus use.

3.2. Modelling of proposed policies

Once-an-hour direct bus from a central location in commuters' suburb, travelling directly to and from the campus (Model 2)

Another binary logistic regression was performed to ascertain the effects of explanatory variables which influence the likelihood of UOW commuters switching to public bus. Table 2 describes the estimated coefficients for policy 1. Gender, age, occupation, frequency of proposed new bus service use and willingness to pay for this service are reported as the significant contributors at a 95% level of confidence ($p < 0.05$) to UOW commuters' mode choice behaviour. The estimated coefficients of gender for switching behaviour to public bus came out negative which indicates that males prefer to switch to proposed direct public bus (DPB) instead of driving. Females were decreased by 23.9% more likely to switch to proposed DPB for commuting to university than males. Older commuters had an increased likelihood of switching to DPB.

Trip distance, travel time, and trip rate were found negative, which implies that an increase in these variables would increase car use though they do not ($p > 0.05$) impact significantly on the switching decision. Because of negative value, for example, an increase in travel time is likely to increase resistance to switching from private car to public bus. On the other hand, frequency of DPB service use and willingness to pay for this service are found to be statistically significant ($p = 0.000$) and positive in sign which indicates a direct relation between them and switching to DPB service, i.e. high likelihood to use this service.

Table 2. Estimation results using binary logistics models (model 2).

	B	S.E.	Sig.	Odds ratio	95% C.I.	
					Lower	Upper
Gender	-.273	.115	.018	.761	.607	.954
Trip distance in km	-.130	.138	.349	1.138	.868	1.493
Travel time in min	-.360	.215	.094	.698	.458	1.063
Trip rate per week	-.188	.388	.627	.828	.387	1.771
Age	-.150	.055	.007	.860	.772	.959
Having license	0.013	.281	.963	1.013	.584	1.758
Occupation (either student of staff)	0.611	.166	.000	1.842	1.330	2.551
Frequency of new service use	1.280	.053	.000	3.597	3.242	3.990
Willingness to pay for new service	0.166	.025	.000	1.181	1.125	1.240
Constant	0.159	.484	.742	1.172		
Summary of statistics						
-2LL				2108.410		
Model chi-square				185.871		
Cox and Snell's R^2				0.320		
Nagelkerke value				0.554		
Hosmer and Lemeshow Chi-square (8)				185.871		
Number of observations				4410		

3.3. Modelling of proposed policies

Park-and-ride service that provided car parking facilities at an urban fringe location around Wollongong where a shuttle bus service connect to campus (Model 3)

Table 3 describes the outputs of the third logistics model (model 3) resulting from policy 2 intervention. The estimated coefficients for gender for using PnR service came out positive, implying that females prefer this service instead of continuing to drive directly to university. The odds ratio increased by approximately 1.198 for female compare to male students. The estimated coefficients for trip distance between the trip origin and UOW was found positive, inferring that even when trip distance is increased, university commuters are most likely to keep their decision on using PnR, i.e. decrease the probability for car users to continue choosing the car as the preferred mode of transport. Trip rate is found significant and negative, signifying that the travel decision is more likely against the use of the PnR service.

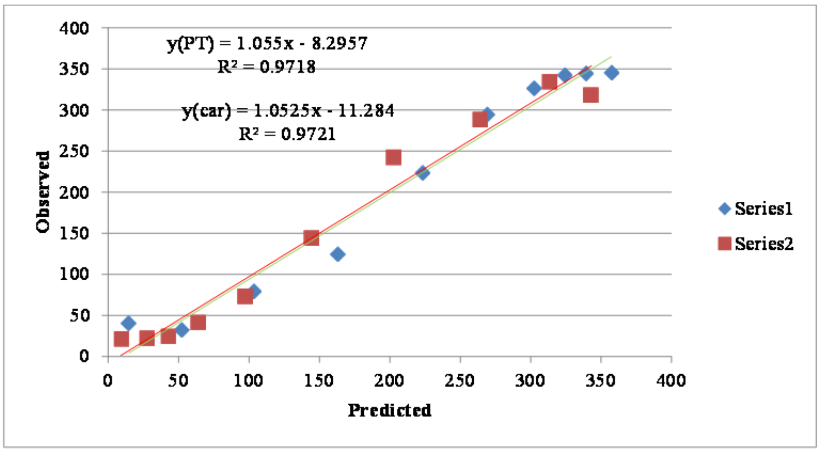
Table 3. Estimation results using binary logistics models (model 3).

	B	S.E.	Sig.	Odds ratio	95% C.I.	
					Lower	Upper
Gender	0.181	.068	.008	1.198	1.048	1.369
Trip distance in km	0.231	.084	.006	1.260	1.069	1.485
Travel time in min	-0.228	.137	.095	.796	.608	1.041
Trip rate per week	-1.433	.263	.000	.239	.142	.400
Age	-0.065	.034	.057	.937	.876	1.002
Having license	-0.493	.126	.000	.611	.477	.782
Occupation (either student or staff)	0.108	.114	.345	1.114	.890	1.393
Frequency of new service use	0.472	.020	.000	1.603	1.541	1.668
Willingness to pay for new service	-0.003	.015	.817	.997	.968	1.026
Constant	0.123	.314	.696	1.131		
Summary of statistics						
-2LL			5357.869			
Model chi-square			622.783			
Cox and Snell's R^2			0.314			
Nagelkerke value			0.523			
Hosmer and Lemeshow Chi-square (8)			622.783			
Number of observations			4410			

3.4. Model validation

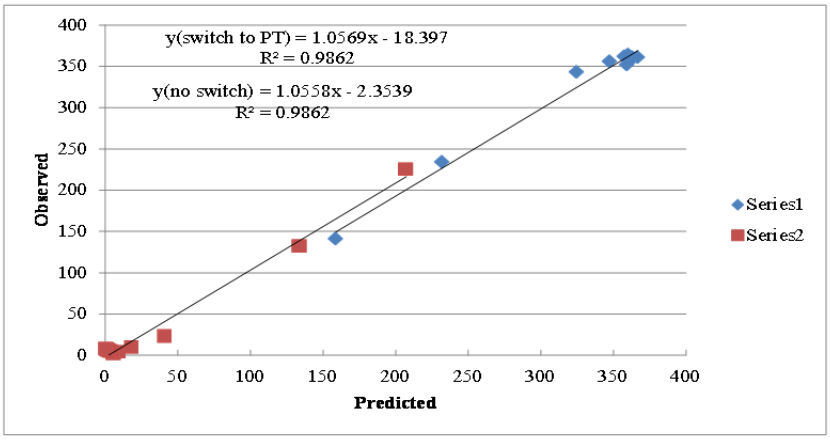
To assess the results, Hosmer and Lemeshow goodness-of-fit test statistic was illustrated and a chi-square test (Table 1, 2 and 3) between the observed and expected frequencies was conducted. It should also be noted that we set the dependent variable as “1” if the commuter travelled by public bus and “0” for car use. In this case, the proposed model is also used to solve a binary classification problem. Because of this, the receiver operating characteristic (ROC) curve is also introduced to evaluate the model performance. The ROC curve illustrates the performance of a binary classifier system as its discrimination threshold is varied. The curve is created by plotting the true positive rate (TPR) against the false positive rate (FPR) at various threshold settings. The true-positive rate is also known as sensitivity. The false-positive rate is also known as the fall-out and can be calculated as (1 - specificity). The ROC curve is thus the sensitivity as a function of fall-out. In this case the sensitivity is the proportion of true positives, given that the decision on switching to new service is present. The specificity is the proportion of true negatives, the proportion of university commuters who remain in their earlier mode of choice i.e. not switching to a new service. Generally speaking, the closer the ROC plot is to the upper left corner, the higher the overall accuracy of the test [17]. Finally, both the Hosmer and Lemeshow test and ROC for three models are shown in Fig. 1-4.

As observed from the goodness-of-fit test, the observed and predicted values for both modes of transport did not differ dramatically, as confirmed by the significant chi-square value and the good fit of the models. The observed and predicted values were very close, which indicates the good fit of the model.



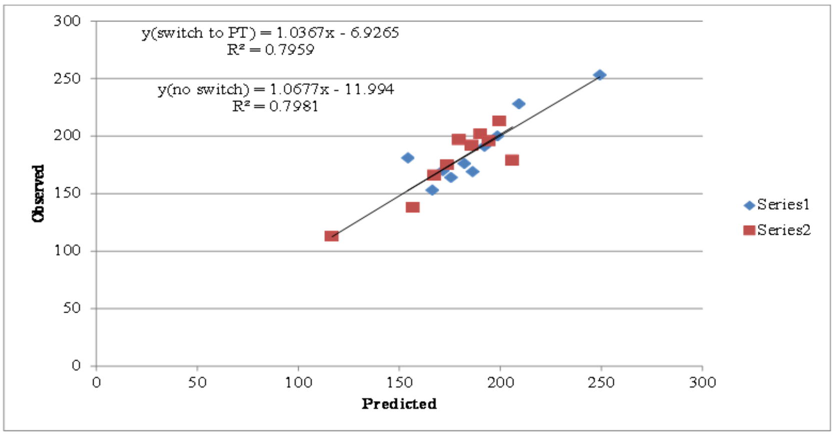
Series 1 = Public bus; Series 2 = Car

Fig. 1. Hosmer & Lemeshow's goodness-of-fit (Model 1)



Series 1 = Switch to new service i.e. bus; Series 2 = Not switch to new service

Fig. 2. Hosmer & Lemeshow's goodness-of-fit (Model 2)



Series 1 = Switch to new service i.e. park n ride; Series 2 = Not switch to new service

Fig. 3. Hosmer & Lemeshow's goodness-of-fit (Model 3)

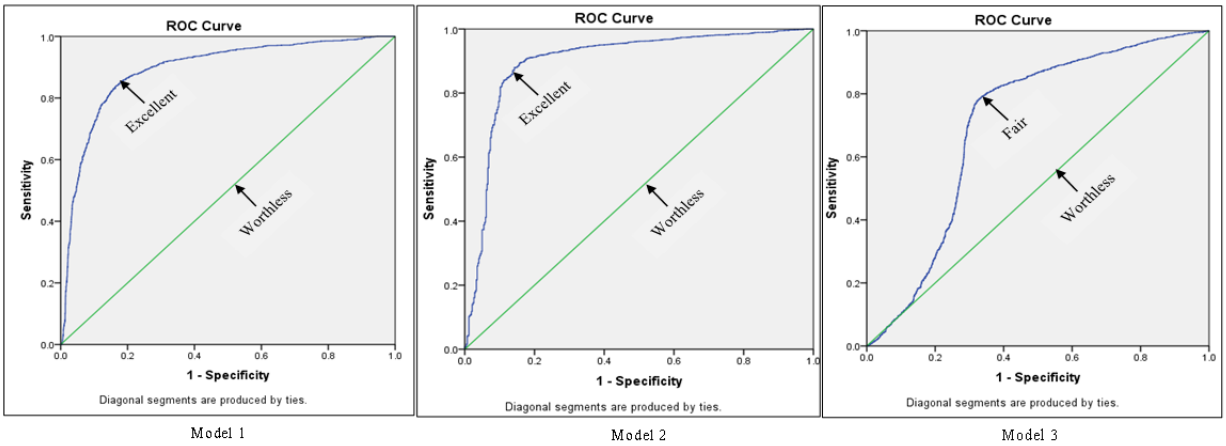


Fig. 4. ROC curve for model validation

The three ROC curves also represent excellent and fair tests plotted on it with reference to worthless curve indicated as a line of 45 degree. The accuracy of the test depends on how well the test separates the group being tested into those with and without the choice in question. Note that the classification accuracy is measured by the area under the ROC curve. An area of 1 represents a perfect test; an area of 0.5 represents a worthless test. For model 1, the area under the curve is 0.902 with 95% confidence interval (0.893, 0.912). The area under the curve is 0.916 with 95% confidence interval (0.902, 0.929) and the area under the curve is 0.735 with 95% confidence interval (0.720, 0.750) for model 2 and 3 respectively. Also, the area under the curve is significantly different from 0.5 since p-value is .000 meaning that the logistic regression classifies the group significantly better than by chance.

4. Probability prediction and modal shift

One of the most important uses of mode choice models is to predict the effects of policy measures on mode choice. To promote the use of public bus, this study examined the incentives as direct bus and PnR service in order to attract UOW commuters from car to public bus use that has the potential to contribute to increase the well-being of UOW commuters as well as surrounding areas. The mode choice probabilities categorised by policy measures are shown in Table 4. The base year market share reflects the share without reflecting policy measures and the probabilities are 36.4% and 63.6% for public bus and private car use, respectively. Once the policy interventions are introduced, a significant modal shift can be seen. . The probability of public bus use increased from 36.4% to 84.4% and 46.6% with policy interventions 1 and 2, respectively.

Table 4. Forecasting changes in traveller mode choice

Mode choice	Base year market share (without policy intervention)	Policy interventions			
		Predicted probability		Modal shift in % from car to bus	
	Model 1	Policy 1 (model 2)	Policy 2 (model 3)	Policy 1	Policy 2
Private car	0.636	0.156	0.534	48%	10.2%
Public bus	0.364	0.844	0.466		

Table 4 presents the base year market shares as well as predicted changes under the condition of policy interventions. The market share changes are predicted by the estimated models with two policy interventions. Results show that the probabilities of public bus use are increased by the introduction of both policies. This implies that both DPB and PnR services have the potential to reduce travel by car with a corresponding increase in public bus use. After integrating these policies, it was found that the probability of private car use has been reduced by a significant amount and the probability of public bus use has been increased to 48% and 10.2% for policies 1 and 2, respectively (Table 4). This confirms that incorporating these services into the current transport system can enhance the overall transport management system in the Wollongong region by increasing the public bus use.

Table 5 shows the case classification results of the logistic regression models. A better model should correctly identify a higher percentage of the cases. According to Model 1, the classification matrices assess if the model fits the data and it was found that the model correctly classified about 90.3% of car cases and about 73.3% of public transport cases. The overall accuracy of the prediction model was 84.1%, indicating that it is a better model. .

Table 5. Classification of mode choice cases[a]

		Model 1			Model 2			Model 3		
Observed		Predicted			Predicted			Predicted		
		Mode choice		% Correct	Mode choice		% Correct	Mode choice		% Correct
		Car	PB		Car	PB		Car	PB	
Mode choice	Car	2531	273	90.3	481	205	70.1	1762	594	74.8
	Public bus	428	1178	73.3	203	3521	94.5	699	1355	66.0
Overall Percentage				84.1			90.7			70.7

a. The cut value is .500

Model 2correctly classified 94.5% of switching decisions and 70.1% of not switching. The overall accuracy of the prediction model was 90.7%.In model 3, it was found that the model correctly classified about 66% of cases using PnR service and about 74.8% of cases not using this service. The overall accuracy of the prediction model was 70.7%. These results illustrate the accuracy of the model.

5. Conclusion

This study investigated the extent to which the mode choice of UOW commuters differs from considering current service to incorporating new transport facilities into the current transport system in Wollongong Area. Binary logit choice models were developed to study the mode choice of UOW commuters. This study contributes to the previous literature on student travel behaviour by analysing a unique data set of UOW commuters. In other words, this study examined the mode choice model of UOW commuters to predict the shifting behaviour by introducing two policy interventions. The utility of transport modes was compared in order to determine the important reasons behind the choice of a particular mode and the circumstances which have the potential to cause UOW commuters to change their commuting choice. In order to promote greater use of public busses, this study examined the effect on car use if once-an-hour direct bus service from home to university (policy 1), and PnR facility (policy 2) at the urban fringe to catch a shuttle bus to university were introduced. The results show that travel time is the most important issue (Model 1) determining the choice of using a car or taking a bus. This was understood by solving the binomial logistics models for probability using several travel attributes. In order to increase public bus use and reduce car dependency, an efficient public bus service system is required. . The results confirmed that direct bus service and PnR service facility near to the bus stop could be implemented to enhance the public bus system in the Wollongong area. The results also indicate that policy 1 (model 2) performs better than policy 2 (model 3). Due to the introduction of policy 1, it was found that almost half (48%) of exiting trips (Table 4) might shift to DPB service. Again, model 2 identified a higher percentage (90.7%) of the cases (Table 5) indicating that it is a better model. A direct public bus service has the potential to make a significant contribution to the reduction of the overall travel time from home to the university campus and therefore, the potential to greatly increase the use of public bus service. Policy 2 has a transfer at the urban fringe area which requires extra time. This is why policy 1 performed better in model 2 than policy 2 in model 3. Finally, the model generated by this research facilitates the public bus travel demand analysis of the UOW. This also aids the government, public transportation agencies, and private carriers in making important decisions and to prevent under- or over-design of their facilities.

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