Analysing the degree of mode captivity in a multi-modal travel behaviour using stated preference data

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1 Introduction

Stated preference (SP) methods are widely employed in travel demand modelling in order to identify the behavioural responses of the population to the introduction of new travelling modes in the study area. These new travelling modes are generally presented to the respondents in the form of SP travel scenarios, where the respondents are asked to state their choice, keeping their current travelling mode and the hypothetical alternatives in mind (Richardson *et al.* 1995).

Various mode choice models have been developed in the past, using the SP data, in order to forecast the mode shares under the hypothetical travel environment (Bradley *et al.* 1988, Gunn *et al.* 1992). However, little has been done to simultaneously analyse the influence of mode captive users, in order to determine their relative influence on the forecasted modal split for the study area. A mode captive user is generally defined as one who does not perceive to use any other alternative than his/her current travelling mode, when presented with hypothetical travelling alternatives. In the past, the models have generally been calibrated using the mode choice survey data only, while that of the captive users was ignored. This yields a knowledge gap in capturing the complete travel behaviour of a region, since the targeted population may contain a significant number of mode captive users. This paper presents a framework developed to analyse the degree of mode captivity in the travel behaviour of the survey respondents, and to determine the influence of these users on the forecasted mode shares.

The southern six suburbs of Redland Shire, Queensland were selected as the study area for this research, namely Capalaba, Redland Bay, Thornlands, Sheldon, Mount Cotton and Victoria Point. The Shire has an estimated population of 130,229 and a high annual population growth rate of around 3 %, compared to 2.4 % for the city of Brisbane (Australian Bureau of Statistics 2007c). The car use in the region is also high by world standards, with approximately three quarters of all personal trips undertaken by car (Socialdata Australia Ltd. 2005). The rising urban sprawl in the region inflates the demand for better public transport infrastructure and services. Keeping this in mind, Redland Shire Council started implementing the Integrated Local Transport Plan (ILTP) that primarily focuses on reducing the car dependency and increasing the market shares of sustainable travelling modes such as walking, cycling and public transport (Queensland Government 2000). The mode shares targeted in the ILTP for the year 2011 (Redland Shire Council 2002) are shown in Table 1, along with the current percentage modal split for journey to work (Australian Bureau of Statistics 2007b).

Table 1 Current mode shares for journey to work (2001 Census) and proposed mode shares (ILTP) for the year 2011 for Redland Shire

	Current Mode Shares	**Targeted Mode Shares**
Car	88 %	69 %
Public Transport	6 %	8 %
Walking	4 %	15 %
Cycling	2 %	8 %

In order to ascertain the practicality of the ILTP targets, stated preference (SP) mode choice surveys were conducted in the study area, in order to forecast the mode shares of the targeted population under the presence of various hypothetical travel alternatives to car. These modes included an efficient and reliable bus on busway network, serviced by a set of five transit access modes of feeder bus, walking and cycling to busway, park and ride, and kiss and ride, and a pair of non-motorised modes of walking and cycling all-the-way. Fractional-factorial designs were implemented in the survey instrument in order to present the respondents with randomly generated levels of modal attributes.

From the high car usage shown in Table 1 for journey to work, it can be concluded that the population of the study area is very likely to contain car captive users, who may not switch to any travelling alternative of car, even with the implementation of a proficient busway, walkway and cycleway network. Hence, it is essential to surmise the influence of car captive users in the study area, on the forecasted mode shares. Contrarily, the statistical analysis conducted on data obtained from Australian Bureau of Statistics (2007a), on the car ownership level, indicated a small, but noticeable, percentage of zero-car households, in each suburb of the study area, as shown in Figure 1. Hence, the targeted population is not likely to contain a considerable number of public transport (PT) captive users, but their influence on the forecasted mode shares, cannot be totally ruled out.

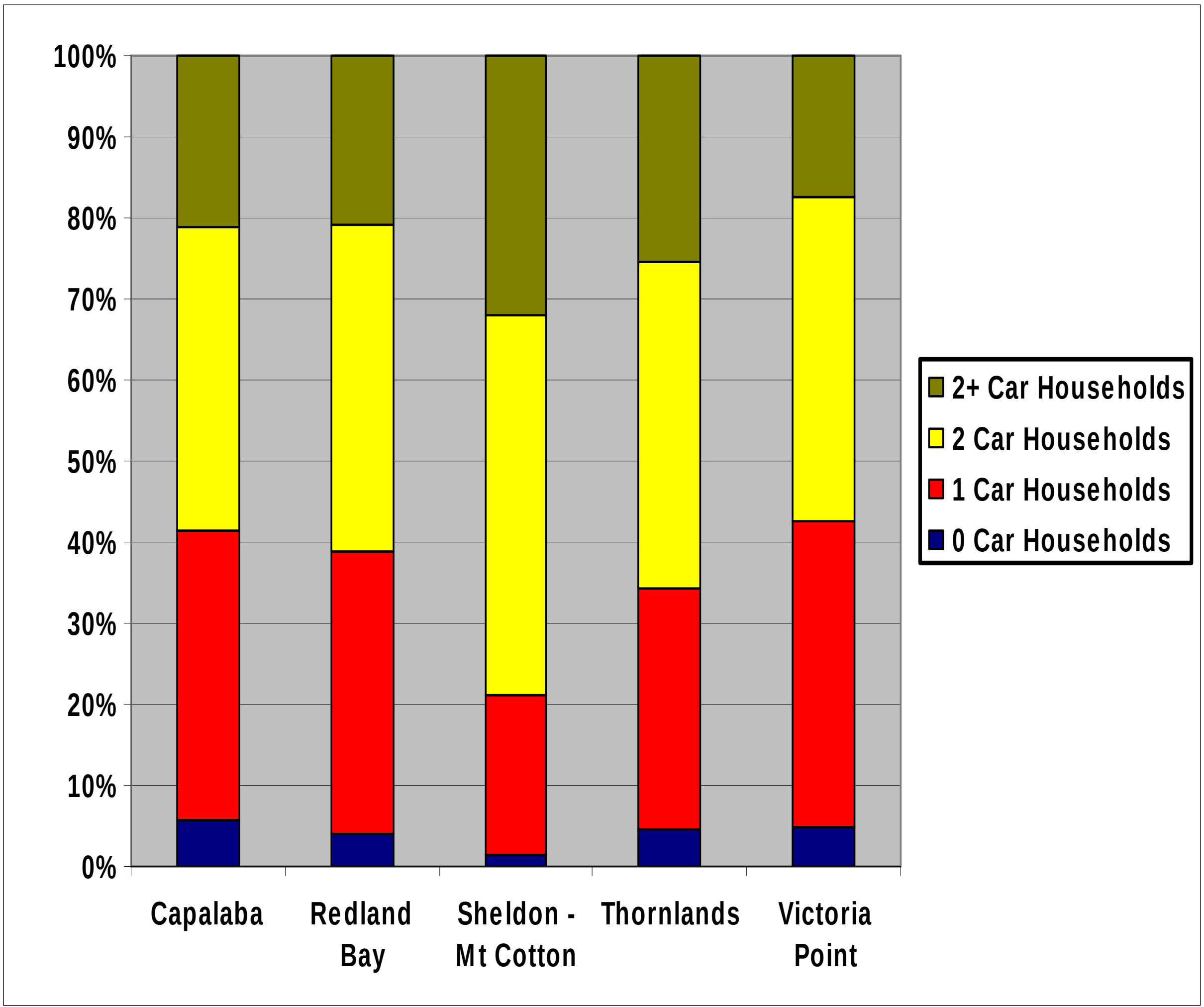

Figure 1 Car ownership levels in the suburbs of the study area

This paper presents the stated preference (SP) survey instrument design implemented in the study area; along with showing the exploratory data analyses conducted on the survey sample in order to determine a pre-modelled travel behaviour of the study area. The paper further discusses the analytical framework developed to identify mode captive and mode choice users in the study area and illustrates the statistical analysis conducted on the car captive data, along with the mode choice modelling results.

2 Stated preference surveys

2.1 Design methodology

Stated preference (SP) surveys offer the opportunity to establish the choices of travellers for existing and proposed transportation modes, under various travel scenarios. The literature on the design of the SP survey instrument is extensive and growing (Ortuzar 1996b, Sanko *et al.* 2002).

In stated preference experiments, the alternatives present within a choice set are defined by the attributes and their levels. It is essential that the survey instrument should present these attributes levels in such a way that the preference for one alternative should not dominate the preferences for all other alternatives. In a choice set where a dominant alternative (or likewise an inferior alternative) exists, the respondents are unlikely to make trade-off between the attributes associated to the travelling modes present. Therefore, in order to identify the respondents who truly perceive to have a choice (mode choice users) and those who do not (mode captive users), an orthogonal fractional-factorial design was implemented.

The physical design of the survey instrument was chosen to be Computer Assisted Personal Interviewing (CAPI) since it is the current state-of-the-art in stated preference (SP) surveys (Stopher and Jones 2003). The survey instrument was designed considering the different types of trip purposes in mind. It began by gathering an individual's revealed preference (RP) travel information regarding the travelling mode he/she selects for a certain trip. The information consisted of various level-of-service modal attributes, and household and car ownership characteristics, found to influence the travel behaviour in previous mode choice studies (Parajuli *et al.* 2005). Based on this data, the instrument was programmed to present the respondent with a particular set of stated preference (SP) games. The use of laptops (notebooks) enabled the feature of generating dynamic SP games which would not have been practical using the conventional paper-and-pencil surveys, where a fixed set of SP games is generally presented irrespective of user's details. The software selected for programming the CAPI tool was WinMint 2.1 (HCG 2000), a standard software used for designing SP surveys.

Each survey was based on the specific trip (work, shopping, education, other) that a respondent makes on regular basis. The SP survey part of the instrument generated eight virtual comparison games between the level-of-service attributes of the mode currently being used by the respondent with that of the perceived alternative mode. The respondent then made a mode-choice (or mode captive) decision by selecting a mode, based on the importance that he/she associates to the attributes of the mode.

Figure 2 presents an example of WinMINT using an SP game to compare the attributes of car and bus on busway under hypothetical scenarios.

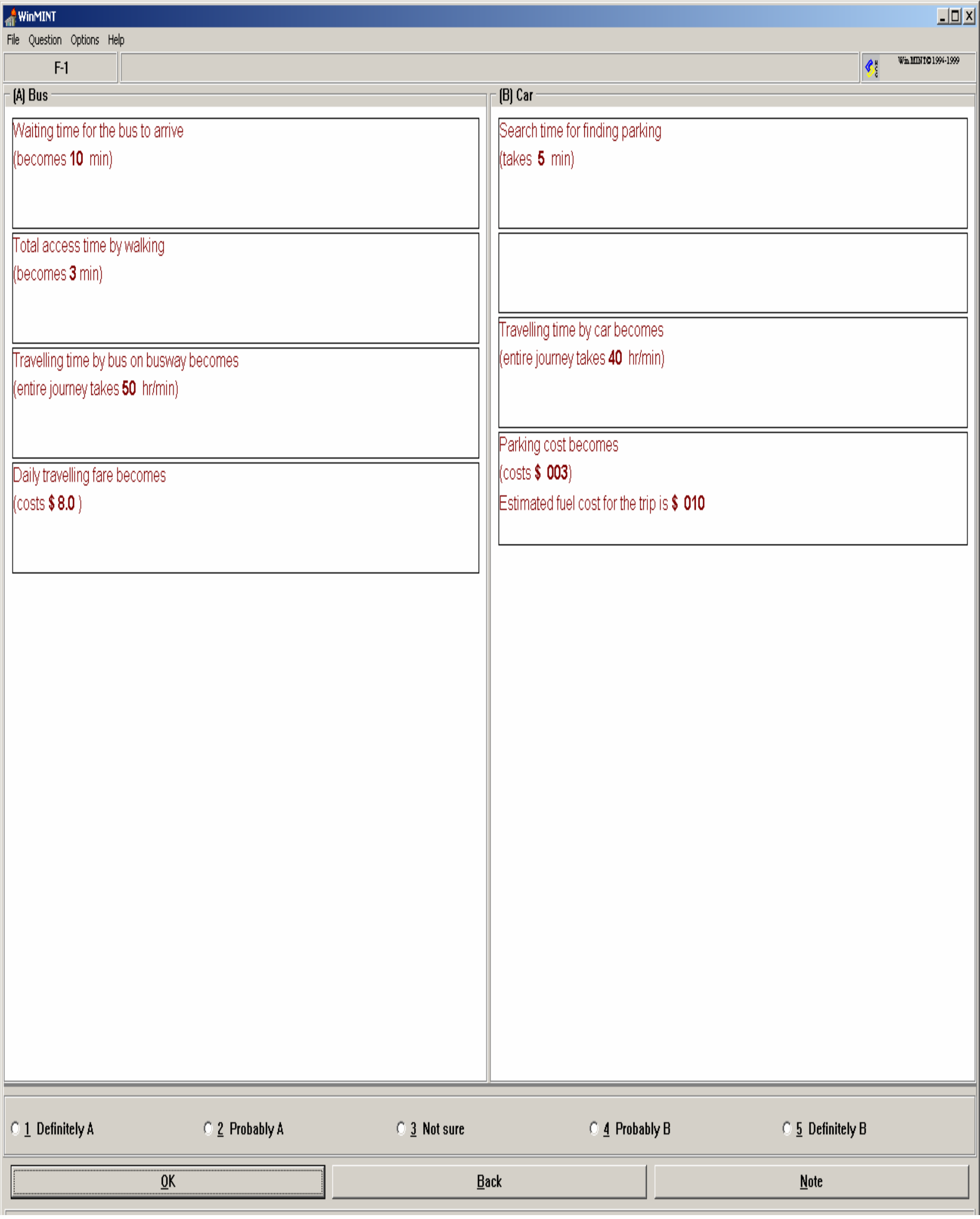

Figure 2 Example of SP Mode Choice Game between Car and Bus on Busway

2.2 Survey implementation and analysis

A sample of 2007 respondents was generated, using the method of stratified random sampling. The strata selected for sampling were the population of each suburb of the study area, and the current modal split of the population for work trips (shown in Table 1). This was done to attain a sample representative of the travel behaviour of population of the study area.

A team of four interviewers was formed in order to conduct the SP surveys in the region using portable laptops. These surveys were conducted within a period of around four months, in addition to one month of pilot surveying.

The data collected from the surveys was categorised on the basis of traveller type, i.e. mode choice and mode captive users. The set of mode captive users was further split into the respondents found captive towards car and public transport. Figure 3 presents the sample split on the basis of traveller type for each trip purpose.

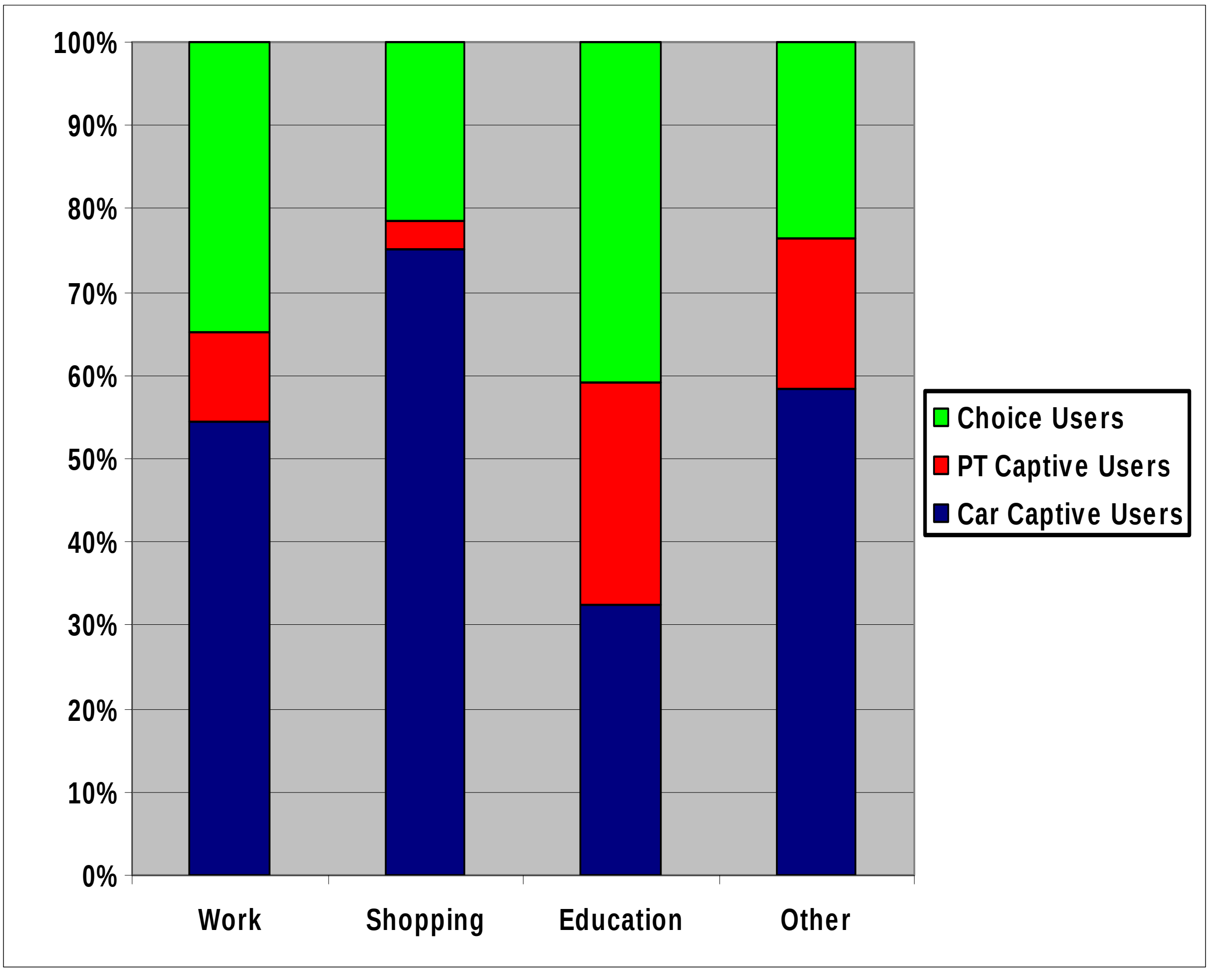

Figure 3 Sample split on the basis of traveller type

Figure 3 clearly indicates that the surveyed sample contains a significant number of car captive users, who do not perceive to switch to any of the hypothetical alternatives to car, presented to them in the SP mode choice scenarios. Hence, analysing the travel behaviour of such type of trip-makers can be highly essential, as they may substantially impact on the future mode shares of the study area. Thus, an analytical framework for mode captive data, separate from that specified for mode choice data, needed to be developed in order to overall surmise the influence of both mode choice and captive users on the travel behaviour, as shown in Section 3.2.

An interesting observation, from the survey results, was that a traveller captive towards a mode for a specific purpose may perceive to have a choice for a different type of trip. For instance, a traveller found captive towards car for shopping trips, may perceive to switch to an alternative mode for travelling to work. Hence, it was essential to determine a set of attributes which may cause an individual to be a mode captive user.

3 Theoretical framework

3.1 Mode choice model development

The literature reveals that the decision to select a particular mode can be equated mathematically in the form of utility functions. The utility of an alternative is defined as the attraction associated with a particular travelling mode from an individual for a specific trip (Abraham and Hunt 1998). As a matter of computational convenience, the utility is generally represented as a linear function of the attributes of the journey weighted by the coefficients which attempt to represent their relative importance as perceived by the traveller. Therefore, one possible representation is given as,

$$U_{ni} = \theta_1 x_{ni1} + \theta_2 x_{ni2} + \ldots\ldots + \theta_k x_{nik} + E_{ni} \qquad (1)$$

where,

U_{ni}	is the net utility function for mode n for individual i;
$x_{ni1}, \ldots, x_{nik}$	are k number of attributes of mode n for individual i;
$\theta_1, \ldots, \theta_k$	are k number of coefficients (or weights attached to each attribute); and
E_{ni}	is the error component (unobserved) of utility of mode n for individual i.

Thus, the choice behaviour can be modelled using the random utility model which treats the utility as a random variable, i.e. comprising of two distinctly separable components: a measurable conditioning component and an error component. Therefore,

$$U_{ni} = V_{ni} + E_{ni} \qquad (2)$$

where,

V_{ni}	is the systematic component (observed) of utility of mode n for individual i; and
E_{ni}	is the error component (unobserved) of utility of mode n for individual i.

Assuming that the unobserved component of utility E_{ni} is independently and identically extreme value I distributed (Ben-Akiva and Lerman 1985), the probability of choosing an alternative mode n, out of M number of total available modes, for individual i can be shown by the following equation,

$$P_{in} = \frac{\exp(V_{in})}{\sum_{m \varepsilon M} \exp(V_{im})} \qquad (3)$$

where,

V_{in}	is the utility function of mode n for individual i;
V_{im}	is the utility function of any mode m in the choice set for an individual i;
P_{in}	is the probability of individual i selecting mode n; and
M	is the total number of available travelling modes in the choice set for individual i.

After testing various model specifications, nested logit models were found to best represent all trip purposes. Figure 4 present a general nested logit model structure developed for the study, in order to estimate the SP mode choice data. However, the model developed for each trip purpose contained a unique specification, based on the perceived vital travelling modes and the associated influential attributes, for that particular purpose. ALOGIT 3.2F (HCG 1992) was used to estimate the nested logit mode choice models.

The selection of the access modes was based on the findings of the literature review done on access mode choice for public transport network (Crisalli and Gangemi 1997, Hubbell *et al.* 1992, Mukundan *et al.* 1991). These access modes also confer with the Integrated Local Transport Plan (ILTP) requirements of the proposed access mode network for public transport in future (Redland Shire Council 2003).

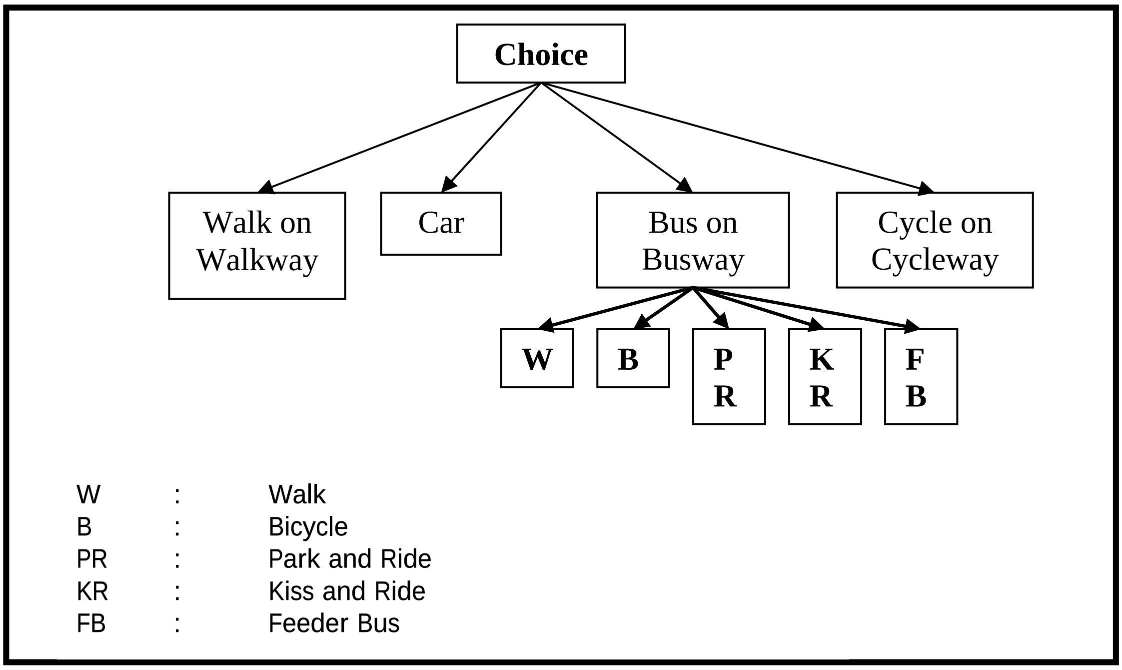

Figure 4 Nested multinomial logit model structures developed for the study

3.2 Mode captivity analysis framework

Despite a few efforts in the past, little has been done to model the mode captive behaviour of a study area, mainly due to the complexities involved in accurately identifying the reasons for an individual to be a mode captive user. For this study, we analysed the degree of mode captivity in the forecasted travel behaviour, with particular focus on car captive behaviour, using the statistical technique of multinomial logistic regression. The detailed theoretical framework of logistic regression functions is presented in (Menard 2001).

Considering multiple predictors X_1, X_2, …, X_m, the probability of being a case P_i, out of *k* number of total unordered outcomes, is given as,

$$P_i = \frac{1}{1 + e^{(\beta_{11}x_1 + \beta_{12}x_2 + ... + \beta_{1m}x_m + \beta_{10})} + e^{(\beta_{21}x_1 + \beta_{22}x_2 + ... + \beta_{2m}x_m + \beta_{20})} + ... + e^{(\beta_{k1}x_1 + \beta_{k2}x_2 + ... + \beta_{km}x_m + \beta_{k0})}} \quad (4)$$

where,

P_i is the probability of outcome *i*;
$x_1, x_2, \ldots, x_m$ are number of predictors;
$B_{i1}, B_{i2}, \ldots, B_{im}$ are regression coefficients of i^{th} outcome; and
B_{i0} are specific constant for i^{th} outcome.

The main assumption in Equation 4 is that all the predictors are independent of each other and associate a linear effect on the regression equation of each outcome. Hence, the data from the set of all outcomes are entered into a single multinomial logistic regression analysis. In the course of the analysis, (k-1) distinct logistic regression functions, all with same *m* predictors, are computed for the *k* sets.

In terms of our research, there can be three possible unordered outcomes; the individuals being mode choice users (i=1), car captive users (i=2) and PT captive users (i=3). Literature review was conducted on determinants of travel behaviour, in order to decide on the predictors to be used in the regression model. In our first attempt, we employed the four attributes of household size (HHSIZE), number of vehicles owned (VEHS), age-group (AGEGR) and trip length (TL) as the main predictors for determining the traveller type of the targeted population. A vital point to note here is that AGEGR was taken as a nominal variable[1]. Hence, for our research, from Equation 4, *k* was set to 3 while *m* was taken to be 4.

For analysing the degree of car captivity in the travel behaviour of the region, Equation 4 was modified to be given as,

$$P_2 = \frac{1}{1 + e^{\theta_1} + e^{\theta_3}} \qquad (5)$$

where,

$$\theta_i = B_{i1}\ \text{HHSIZE} + B_{i2}\ \text{VEHS} + B_{i3}\ \text{AGEGR} + B_{i4}\ \text{TL} + B_{i0} \qquad (6)$$

Similarly, the degree of public transport (PT) captivity in the travel behaviour of the region was analysed using the following equation,

$$P_3 = \frac{1}{1 + e^{\theta_1} + e^{\theta_2}} \qquad (7)$$

From Figure 3, it was observed that mode captivity can vary with trip purposes of the same individual. Therefore, equations 5, 6 and 7 were uniquely estimated for each trip purpose, in order to analyse the degree of mode captivity for each set of trips, using SPSS 15.0 (S.P.S.S. Inc. 2006), a standard computer-based tool for statistical analysis.

4 Modelling results

The results obtained from the mode choice model estimations and statistical analysis from the survey data are discussed below.

4.1 Mode choice models

A set of *2007* stratified randomly sampled respondents were surveyed as part of this study, out of which *520* were found to be mode choice users for all trip purposes. Each respondent provided choice responses for 8 mode choice games; thus resulting in a total of *4160* SP observations. Table 2 presents the split of these observations on the basis of four trip purposes.

After conducting various model estimation runs on all trip purposes, all models were found to be best represented using the nested multinomial logit structure, with a tree structure which distinguishes between car, public transport and non-motorised modes, as shown in Figure 4.

[1] AGEGR -> 1 represents individuals under 18 years of age
2 represents individuals from 18 to 45 years of age
3 represents individuals from 46 to 59 years of age
4 represents individuals over 59 years of age

The trip purposes were further categorised and re-modelled on the basis of two trip lengths, *regional* and *local*, in order to determine the variation in travel behaviour of the trip-makers with the change in travel distance. Regional trips represented trips undertaken by the population of the study area destined for Brisbane City, or via city corridors, while the local trips represented the trips taken within the Shire.

Table 2 Split of SP mode choice observations on the basis of trip purpose

Trip Purpose	**Number of SP Observations**
Work	1362
Shopping	1040
Education	544
Other	1214
TOTAL	**4160**

Various level-of-service modal attributes and household parameters were tested with the utility functions associated with each travelling mode, and assessed on the basis of the t-ratio values and magnitude of standard error obtained from the estimation runs. The final model estimation results for regional work trips are presented in Table 3.

A satisfactory overall goodness-of-fit value was determined for regional work trips, which was also consistent with previous logit modelling studies done for work trips in other parts of the world (Dissanayake and Morikawa 2002, Jovicic and Hansen 2003, Ortuzar 1996a) where the ρ^2 values were found to lie between 0.4 and 0.6 for similar model specifications and choice sets.

The magnitude of the standard errors of the estimated coefficients, compared with the magnitude of the estimated coefficients, was found to be relatively small for all level-of-service attributes, but was comparatively high for some mode-specific constants, particularly that estimated for kiss and ride.

It was observed that the coefficients of all the level-of-service times were quite stable, particularly the coefficients of in-vehicle travel times (TT) for each mode in the SP choice set. On the other hand, the mode-specific constants appeared to be relatively less stable with high magnitude of standard error, but proving statistically significant due to their high magnitude of t-ratios at 95% confidence interval.

The coefficients of waiting times were found to be significant for the two car access modes (park and ride and kiss and ride to bus on busway), implying that the respondents walking or riding a feeder bus to the busway station do not perceive waiting time as an influential attribute for their mode choice. The surprising result was that the signs of the coefficients of the access times *for* park and ride and kiss and ride were estimated to be positive, indicating that if the time to access the busway station increases for all transit modes, the respondents using bus on busway will have a shift in the mode choice towards car driven access modes.

The values of time (VOTs) were also calculated, by taking the ratios of the coefficients of in-vehicle travel time and travel cost, for the relevant travelling modes, as shown in Table 4. Note that the attribute of travelling cost for car was estimated as the sum of the fuel cost, parking cost (if any) and car maintenance cost (taken as 10% of the fuel cost) for the specific trip purpose. Hence, the VOT, shown in Table 4, is a true representation of an individual's perceived value of time for each trip purpose. The VOT for the mode of kiss & ride could not be estimated, since the coefficient for travelling time was determined to be insignificant from zero for the particular mode, for regional work trips.

Table 3 Nested logit model estimation results for regional work trips

Alternatives	Attributes	Coefficients	T-Ratio	Standard Error
Car as Driver	In-vehicle travel time	-0.06222	-2.8	0.02220
	Travel cost	-0.00320	-1.6	0.00022
	Mode-specific constant	-1.61900	-2.1	0.78800
Car as Passenger	Mode-specific constant	-8.20100	-4.5	1.83000
Feeder Bus to Bus on Busway	In-vehicle travel time	-0.06286	-2.8	0.02280
	Trip fare	-0.00503	-2.6	0.00270
	Mode-specific constant	-5.08200	-5.0	1.01000
Walk to Bus on Busway	In-vehicle travel time	-0.06887	-3.9	0.01790
	Trip fare	-0.00386	-3.3	0.00235
	Access time	-0.26870	-5.4	0.04930
Park & Ride to Bus on Busway	In-vehicle travel time	-0.08684	-4.1	0.02090
	Trip fare	-0.00583	-3.4	0.00286
	Waiting time	-0.21650	-3.6	0.06000
	Access time	0.52120	5.0	0.10400
	Mode-specific constant	-2.49800	-2.5	0.99700
Kiss & Ride to Bus on Busway	Trip fare	-0.01219	-3.3	0.00365
	Waiting time	-0.31500	-2.5	0.12800
	Access time	0.76140	4.5	0.16800
	Mode-specific constant	-7.39300	-3.6	2.05000
Car	Scale parameter	0.94980	2.6	0.36000
Bus on Busway	Scale parameter	0.47710	3.4	0.14000
ρ^2		0.4766		
Number of SP Observations		680		

Table 4 Value of Time (VOT) for travelling modes for regional work trips

Travelling Modes	Value of Time ($/hr)
Car as Driver	11.67
Feeder Bus to Busway	7.50
Walk to Bus on Busway	10.71
Park & Ride to Bus on Busway	8.94

The value of time for car as driver mode was estimated to be higher than those determined for bus on busway modes, indicating that the car users value their time more than other trip-makers. Nevertheless, the VOT for walk to bus on busway mode was found to be fairly closer to that for car as driver mode, indicating that the mode choice users perceive to switch to the specific alternative to car, if a walk to busway network functioning with competing attributes values to that of car, as shown to them in the SP mode choice scenarios, can be implemented in practice.

4.2 Mode captivity analysis

Multinomial logistic regression runs were conducted for all trip purposes to estimate the unknown coefficients shown in Equation 6.

First, we analysed the degree of car captivity in travel behaviour for each trip purpose, by selecting the specific outcome as our reference category. Tables 5 to 12 show the values of the estimated coefficients associated to the outcomes of mode choice and PT captive users for all trip purposes, with the outcome of car captive users being a reference category.

The first criteria generally employed in ascertaining the adequacy of the values of the estimated logistic regression coefficients is the overall p-value, indicating if the logistic function associates a good fit and whether the variables associate a high explanatory power. The tables 5 to 12 show that the overall p-value determined for each trip purpose was highly satisfactory (Cohen *et al.* 2003), except for education trips where the p-values were observed to be considerably higher than 0.05. The main reason for inadequate p-values for education trips can be attributed to the relatively small sample size determined for the survey. Thus, the degree of car captivity was analysed for the regional and local trip records for work, shopping and other trip purposes.

The attribute of the number of vehicles per household (VEHS) was found to be significant for all trip purpose, and was observed to substantially drive the perception of the targeted population regarding their traveller type as compared to other attributes shown in Equation 6. The sign of VEHS was determined to be negative, with high magnitude, for most trip purposes, indicating that as the number of vehicles in the household increases, the possibility of the trip-maker being a mode choice user or PT captive decreases significantly. For regional other trips, for instance, it was determined that if the number of vehicles in the household increase by even one, it becomes 0.99 (exp (-0.008) = 0.99) times less likely for the traveller to be a PT captive user.

The regression intercepts were also determined to be significant; however, they may not have as astounding impact as the mode-specific constants have on the mode choice of a trip (Cohen *et al.* 2003).

An interesting finding was that the parameter of household size (HHSIZE) was determined to be insignificant for PT captive users, for all trip purposes. It indicates that the attribute does not play a vital role in the traveller type outcome of an individual being a PT captive, and thus, the variation in the parameter value will not substantially impact on the individual's perception regarding his/her traveller type. Similarly, the possibility of an individual perceiving to have mode choice for any trip purpose did not seem to be affected by his/her age-group (AGEGR). It shows that an individual can perceive to have a mode choice for a certain type of trip, irrespective of his/her age.

The sign and significance levels of the attribute of trip length (TL) was found to vary with the likelihood of outcomes and trip types. For local other trips, for instance, a 1 km. increase in the travel distance seemed to reduce the outcome of an individual being a PT captive user by 0.99 (exp (-0.004) = 0.99) times. On the other hand, for local work trips, the likelihood of the traveller being a PT captive user increases by 1.10 (exp (0.093) = 1.10) times with every added kilometre in the journey, indicating that the trip-makers are more likely to switch to the travelling alternatives for car, for *work* trips as compared to *other* trips undertaken within the Shire.

After examining the adequacy of the values, signs and significance levels of estimated regression coefficients associated to the mode choice and PT captive outcomes, the probability of an individual being a car captive was analysed for all trip purposes. Equations 8 to 13 present the probability functions of a traveller being a car captive user for regional work, local work, regional shopping, local shopping, regional other and local other trips respectively.

$$P_1 = \frac{1}{1 + e^{((-1.996*VEHS)+2.958)} + e^{((-0.926*VEHS)+(-0.729*AGEGR)+(0.035*TL))}} \quad (8)$$

$$P_1 = \frac{1}{1 + e^{((-3.344*VEHS)+5.781)} + e^{((-3.624*VEHS)+(0.093*TL)+3.465)}} \quad (9)$$

$$P_1 = \frac{1}{1 + e^{((-3.214*VEHS)+(-0.124*TL)+8.307)} + e^{((0.206*TL)-7.494)}} \quad (10)$$

$$P_1 = \frac{1}{1 + e^{((-0.313*HHSIZE)+(-3.620*VEHS)+(0.062*TL)+4.659)} + e^{((1.332*AGEGR)-7.747)}} \quad (11)$$

$$P_1 = \frac{1}{1 + e^{((-0.956*VEHS)+(-0.021*TL)+2.454)} + e^{((0.404*AGEGR)+(-0.021*TL))}} \quad (12)$$

$$P_1 = \frac{1}{1 + e^{((-0.304*HHSIZE)+(-2.590*VEHS)+2.834)}} \quad (13)$$

Table 5 Car captive analysis for regional work trips

	Attributes	Coefficients	Std. Error	P-value
	B_{10}	2.958	1.100	0.007
Mode	HHSIZE	-0.176	0.131	0.178
choice	VEHS	-1.996	0.261	0.000
users	AGEGR	-0.087	0.283	0.760
	TL	0.013	0.015	0.386
	B_{30}	1.245	1.207	0.302
PT	HHSIZE	-0.083	0.149	0.580
captive	VEHS	-0.926	0.257	0.000
users	AGEGR	-0.729	0.331	0.028
	TL	0.035	0.015	0.018
Overall P-value		0.000		

Table 6 Car captive analysis for local work trips

	Attributes	Coefficients	Std. Error	P-value
Mode choice users	B_{10}	5.781	1.422	0.000
	HHSIZE	-0.115	0.182	0.528
	VEHS	-3.344	0.398	0.000
	AGEGR	-0.292	0.318	0.359
	TL	0.038	0.028	0.179
PT captive users	B_{30}	3.465	2.040	0.089
	HHSIZE	0.227	0.266	0.394
	VEHS	-3.624	0.623	0.000
	AGEGR	-0.741	0.533	0.164
	TL	0.093	0.033	0.006
Overall P-value		0.000		

Table 7 Car captive analysis for regional shopping trips

	Attributes	Coefficients	Std. Error	P-value
	B_{10}	8.307	3.655	0.023
Mode	HHSIZE	-0.485	0.481	0.314
choice	VEHS	-3.214	0.800	0.000
users	AGEGR	-0.094	0.654	0.886
	TL	-0.124	0.074	0.093
	B_{30}	-7.494	4.551	0.100
PT	HHSIZE	-0.612	0.760	0.421
captive	VEHS	0.032	0.555	0.954
users	AGEGR	0.145	0.711	0.839
	TL	0.206	0.062	0.001
Overall P-value		0.000		

Table 8 Car captive analysis for local shopping trips

	Attributes	Coefficients	Std. Error	P-value
Mode choice users	B_{10}	4.659	1.162	0.000
	HHSIZE	-0.313	0.160	0.050
	VEHS	-3.620	0.343	0.000
	AGEGR	-0.064	0.232	0.783
	TL	0.062	0.033	0.059
PT captive users	B_{30}	-7.747	2.809	0.006
	HHSIZE	-0.163	0.344	0.635
	VEHS	0.033	0.456	0.942
	AGEGR	1.332	0.589	0.024
	TL	0.022	0.058	0.707
Overall P-value		0.000		

Table 9 Car captive analysis for regional education trips

	Attributes	Coefficients	Std. Error	P-value
	B_{10}	4.977	3.059	0.104
Mode	HHSIZE	-0.855	0.458	0.062
choice	VEHS	-0.532	0.448	0.235
users	AGEGR	-0.396	0.765	0.605
	TL	0.005	0.049	0.921
	B_{30}	0.914	2.428	0.706
PT	HHSIZE	-0.150	0.336	0.656
captive	VEHS	-0.439	0.386	0.255
users	AGEGR	0.354	0.688	0.606
	TL	0.009	0.040	0.828
Overall P-value		0.282		

Table 10 Car captive analysis for local education trips

	Attributes	Coefficients	Std. Error	P-value
Mode choice users	B_{10}	1.545	1.287	0.230
	HHSIZE	0.472	0.241	0.05
	VEHS	-1.720	0.344	0.000
	AGEGR	-0.424	0.332	0.202
	TL	-0.002	0.052	0.977
PT captive users	B_{30}	2.597	1.677	0.122
	HHSIZE	0.564	0.285	0.048
	VEHS	-0.603	0.327	0.065
	AGEGR	-3.068	1.050	0.003
	TL	-0.092	0.066	0.163
Overall P-value		0.049		

Table 11 Car captive analysis for regional other trips

	Attributes	Coefficients	Std. Error	P-value
	B_{10}	2.454	0.890	0.006
Mode	HHSIZE	-0.142	0.131	0.279
choice	VEHS	-0.956	0.157	0.000
users	AGEGR	-0.142	0.187	0.446
	TL	-0.021	0.006	0.001
	B_{30}	-0.751	0.905	0.407
PT	HHSIZE	-0.112	0.125	0.372
captive	VEHS	-0.008	0.140	0.954
users	AGEGR	0.404	0.184	0.028
	TL	-0.021	0.006	0.001
Overall P-value		0.000		

Table 12 Car captive analysis for local other trips

	Attributes	Coefficients	Std. Error	P-value
Mode choice users	B_{10}	2.834	1.239	0.022
	HHSIZE	-0.304	0.178	0.088
	VEHS	-2.590	0.361	0.000
	AGEGR	0.245	0.251	0.329
	TL	-0.022	0.036	0.530
PT captive users	B_{30}	-0.583	1.531	0.703
	HHSIZE	-0.357	0.238	0.133
	VEHS	-0.227	0.324	0.482
	AGEGR	0.014	0.311	0.964
	TL	-0.004	0.032	0.898
Overall P-value		0.000		

The probability of being a car captive user was evaluated for each trip purpose, using certain values for the set of significant attributes. For example, the probability of a 20 year old traveller, having 2 cars in his/her 4-person household, of being a car captive user for undertaking a local shopping trip, 4.5 kilometres from his/her trip origin, is calculated to be approximately 97%. On the other hand, if a 50 year old person with no cars in his/her 1-person household conducts the same trip, 2 kilometres from his/her trip origin, the probability of him/her being a car captive user is computed to be around 1%. In other words, it is not possible for the latter to be a car captive user for local shopping trips, since he/she does not own a vehicle. Similar statistical analyses were conducted for all other trip purposes, in order to ascertain the degree of influence each attribute associates in the car captive travel behaviour of the population of the study area.

5 Conclusions

In this paper, we have presented a statistical framework to analyse the degree of mode captivity in a multi-modal travel environment. Since no standard mode captive models have been implemented to date, this framework serves as a transitional step to model mode captive data and ascertain its influence on the forecasted travel behaviour.

Computer-based stated preference (SP) surveys were conducted in Southern Redland Shire, Queensland, presenting the respondents with eight randomly generated SP mode choice games. Based on these responses, an individual was determined to be a mode captive or mode choice user. The set of mode captive users was further split into car captive and PT captive users.

Out of the 2007 respondents surveyed, approximately 60% were determined to be car captive users; i.e. not perceiving to switch to any travelling alternative to car, shown to them in the SP survey. Nested logit models were then estimated, using the mode choice data only, for four trip purposes of work, shopping, education and other trips. The trip purposes were further categorised on the basis of two trip lengths, regional and local trips, resulting in the estimation of eight unique mode choice models to forecast the mode shares of the targeted population. The model specification developed for the mode choice module comprised of the hypothetical travelling alternatives to car, namely bus on busway, walk on walkway and cycle to cycleway. The bus on busway mode further associated a set of five transit access modes of feeder bus, walking and cycling to busway, park and ride, and kiss and ride.

For analysing the degree of car captivity in the travel behaviour of the region, multinomial logistic regression equations were developed, based on the three socio-demographic characteristics of household size, number of vehicles per household and age-group of the individuals, along with the level-of-service parameter of trip length. Logistic regression runs were conducted, using SPSS 15.0 (S.P.S.S. Inc. 2006), for each trip purpose to determine the significant parameters influencing the three possible outcomes of an individual; being a mode choice, car captive or PT captive user.

The analysis showed that the attribute of number of vehicles per household (VEHS) served as the driving determinant for the traveller type outcome of an individual for each trip purpose. With a unit increase in the number of vehicles in the household, the likelihood of the traveller being a mode choice or PT captive user was found to reduce substantially for each trip purpose. Various probability functions were also tested with varying values of parameters, in order to observe the possible changes in the outcomes of traveller type.

Extensive statistical analyses on various socio-demographic attributes such as income, gender, etc. are planned to be conducted in near future, in order to develop a better understanding of the travellers' perception towards car and its alternatives. Additionally, we plan to develop a framework to test various ordinal and nominal parameters, such as comfort and convenience, and availability of public transport service.

6 Future directions

From the findings of this study, we plan to further extend the statistical framework, in order to better comprehend the travellers' perception and test various behavioural attributes. The main research tasks planned in near future are listed as follows,

- Several socio-demographic characteristics such as income, gender, etc, and nominal variables such as comfort and convenience, and availability of public transport service need to be tested to determine their influence on the mode captive behaviour of the population of the study area; and
- The literature on developing nested binary logistic regression equations is currently under review, with the initiative of improving the statistical framework for analysing the degree of mode captivity in travel behaviour, by employing a hierarchical structure, with the nests being mode choice and mode captive users. The nest of mode captive users can then be branched further to car captive and PT captive users.

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