IDENTIFYING DRIVER TACTICS FOR INTERACTING WITH A REAL-TIME TYRE INFORMATION SYSTEM

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ABSTRACT

This paper investigates the sensitivity and preference heterogeneity of individuals in respect of a new Real-Time Tyre Information System (RTTIS). By using the attitudinal indicator, a latent class model framework is developed. Estimates for a three-class model are discussed in detail to illustrate the potential of this approach in characterising the customer segments and preferences for an innovative vehicle technology. The results offer clear evidence of the preference heterogeneity across classes. The analysis further shows that the survey response duration has a strong explanatory power with respect to class membership.

Keywords: latent class model, preference heterogeneity, survey response duration, real-time tyre information system

1. INTRODUCTION

Among many factors, proper tyre pressure contributes considerably to a vehicle's on-road safety and operating efficiency, which in turn impact on its CO_2 emissions. Triggered by the Ford/Firestone crisis (Greenwald, 2001), the Tyre Pressure Monitoring System (TPMS) is being made mandatory in the United States by the enactment of the TREAD Act 2000 (USC, 2000; NHTSA, 2005). The European Parliament has also proposed a regulation to make TPMS mandatory, which will take effect in 2012 (Álvarez, p. 9, 2008).

However, according to a recent survey in Australia, it appears that drivers lack the basic knowledge of tyres, such as the suggested interval for checking tyre pressures and that tyre pressure maintenance remains a low priority (Bearepaires, 2008). To some extent, this phenomenon can be explained by lack of prompt information on tyre pressure and the action alternatives for inflating under-pressure tyres.

The Tyre Pressure Monitoring System is a built-in or retro-fitted device to monitor the air pressures inside vehicle tyres. It has the capability of presenting real-time information on tyre pressures on the dashboard or other display equipment. It was first introduced into cars by Porsche in late 1990s. By 2008, some car manufacturers such as AUDI, BMW, Mercedes-Benz, and OPEL have equipped all car models with the TPMS. Others including Alfa-Romeo, Citröen, FIAT, Ford, Peugeot, Renault and Volkswagen have installed the device on some of their cars.

As an extension to the TPMS, a Real-Time Tyre Information System (RTTIS) becomes technically feasible to integrate the TPMS, the Global Positioning System and the Traffic Message Channel to provide real-time information on tyre pressures and the consequent impacts on the vehicle's operating efficiency under the specific conditions the vehicle is experiencing. So far, progress in understanding driver responses to these systems has been far behind the pace of technology advances. This knowledge is a key to realisation of the expected improvement of the operating efficiency and safety of a vehicle equipped with the RTTIS.

The objective of this paper is to understand the interaction between drivers and a new RTTIS. The paper investigates the sensitivity of drivers with respect to the information provided through the RTTIS. A latent class model is developed to identify the heterogeneity of drivers' responsiveness to tyre pressure information. These issues are relevant to the RTTIS design and the marketing of a particular specification of the RTTIS to the right driver segment.

The remainder of this paper is organised as follows. Section 2 discusses the rationale for the use of the latent class model, and presents a specific framework for the latent class model. This is followed by a brief account of the data collection in Section 3. Section 4 presents a descriptive analysis of the data. Final section draws conclusions.

2. METHODOLOGY

2.1. The use of the latent class model

Among various choice models, the latent class model (LCM) and the mixed logit model (ML) are probably the two best candidates to improve the multinomial logit model (MNL) in accommodating the preference heterogeneity across individuals (Greene and Hensher, 2003; Hess et al., 2009; McFadden and Train, 2000). In essence, the ML specifies the random parameters to follow a continuous joint distribution (Train, 2009). The LCM can be seen as a special case of the ML where a step function with a finite number of steps is used to approximate the continuous curve (McFadden and Train, 2000; Swait, 1994; Swait, 2009; Train 2009).

The specification of a LCM includes an iterative process of determining the number of latent classes outside the estimation process and some statistical measurements of goodness-of-fit can be used to decide the most suitable number of classes. In contrast, the specification of a ML involves challenging tasks of determining which parameters among the full set are assumed to be random and what distributions they follow. However, the specificity of the distribution assumptions in the ML can be counterbalanced by its flexibility or robustness to accommodate a range of assumed distributions for the selected parameters (Greene and Hensher, 2003), which in fact alleviates the seeming burden of model specification. Moreover, both the LCM and the ML improve significantly in log-likelihood against the multinomial logit model (MNL), due to the relaxation of the assumption of preference homogeneity, and the magnitude of improvements in both models are comparable (Hess et al., 2009). Because of the fact that these two models are not nested, a difference in the log-likelihood functions does not necessarily lead to a model being superior to the other (Greene and Hensher, 2003). To summarise, it is hard to conclude statistically that one or the other of the two specifications is preferable. As a result, in this study considerations from other perspectives are needed to decide which model is suitable for modelling the sensitivity and heterogeneity across driver responses.

A LCM is chosen in this study due to two considerations. The first is that the specification of a LCM has a close correspondence to the concept of market segmentation (Train, 2009). The LCM can come up with a set of parameters specific to individuals, and groups the full set into a finite number of classes, with the parameter values across individuals within a class being statistically homogeneous and those between classes heterogeneous. In this study, each class in the LCM can be interpreted as a market segment of drivers, who have homogenous sensitivity to those features of the RTTIS that are statistically significant. In general, the number of classes is small, being two, three or four in some applications (Bhat, 1997; Boxalland Adamowicz, 2002; Gupta and Chintagunta, 1994; Jones and Hensher, 2007) and up to five or six (Kamakura and Russell, 1989; Moors and Vermunt, 2007).

The second consideration is to identify the factors that cause the heterogeneity between classes. Traditionally this has focused on preference differences between classes (Train 2009) under the utility maximisation regime. However, as will be discussed in Section 2.2, one possible source of the differences is the low quality of data records from some respondents and the LCM can identify those respondents.

2.2 Framework for the latent class model

The formulation of the latent class model for the above choice situation follows the general framework developed by McFadden (1986), put into operation by Swait (1994) in modelling choice behaviour of beauty products and then followed by others such as Boxall and Adamowicz (2002) in wilderness recreation. The essential part of the framework is to incorporate confirmatory factor analysis into a discrete choice model to discover those unobserved attitudinal and perceptual factors or constructs that help to explain the heterogeneity across individuals in making a choice. The LCM has two components. The first part is a latent class membership model, which takes the indicators of attitudinal and perceptual factors and some socio-demographic characteristics of individuals as explanatory variables to come up with the probabilities for individuals to be affiliated with particular classes. The other part is a discrete choice model that produces the probabilities for individuals to choose alternatives conditional on their memberships.

In this study, once the in-vehicle RTTIS detects any under-inflated tyre, it starts beeping and displaying relevant information on the screen. Then, an individual can choose an alternative from two options:

1. Action – go to a petrol station to inflate tyres during the current trip, or
2. No action – no action during the current trip.

The information displayed is featured by its contents, manner of expression and others, depicting a situation in which an individual needs to choose one of the two alternatives. These variables give the features of the information rather than the attributes of the choice alternatives.

As will be discussed later, the choice information was collected through a self-administered online survey. The time that a respondent spent on each of the questions was implicitly recorded by the background software. Thus, the survey response duration (SRD), which is defined as the elapsed time between the respondent's pressing the start button and completing the last question in the survey, can be calculated.

Some important issues associated with the SRD for online surveys have recently been investigated. Yan and Tourangeau (2008) discovered that the complexity of online survey questionnaires and characteristics of respondents (such as age, education, experience with the Internet, and the number of surveys done) have impacts on the SRD. Malhotra (2008) found that under certain circumstances the shorter the SRD is, the less quality the data records of online respondents have, and that some respondents exhibit symptoms of satisficing behaviour during surveys, such as choosing the first options irrespective of their contents (Galesic et al., 2008), agreeing with any assertion made in the questionnaire and endorsing the status quo (Krosnick, 1991). In the context of the LCM, a decision maker is assumed to choose an option among several actions that maximises the corresponding utility and the heterogeneity across classes is interpreted as being caused by preference differences. However, when some respondents do not spend sufficient times to read the contents of various choices but to choose a particular option irrespectively, they do not behave as a utility maximiser but a utility satisficer. A satisficer is less persistent than a maximiser to spend time to acquire information on choice options and to figure out their consequences, and the choice made by a satisficer is more likely to be satisfactory (Simon, 1955), which is to answer all questions on the survey questionnaire and then to receive a gift voucher in this study. Consequently, the interpretation that the parameters estimated through a utility maximisation framework, such as the LCM, are behavioural preferences is valid for utility maximisers but invalid for utility satisficers.

Considering the possibility of the presence of utility satisficers and the technical feasibility of recording the times that respondents spend on the survey, the SRD is chosen as an attitudinal indicator to capture the amount of willingness, commitment and psychological and physiological capability of respondents during the survey (Der and Deary, 2006; Malhotra, 2008).

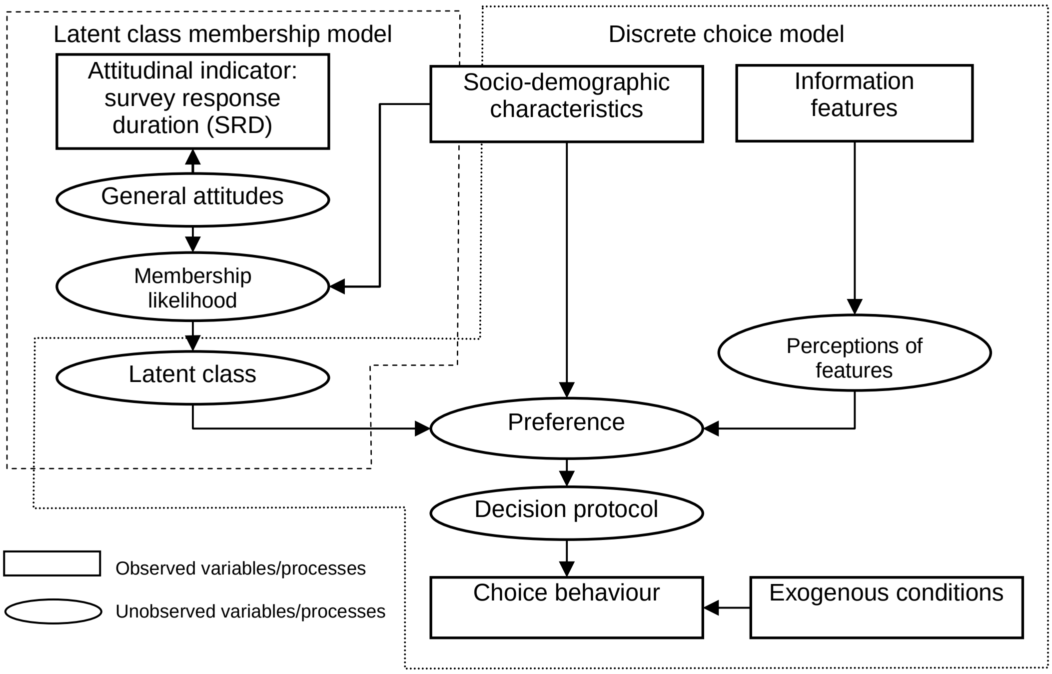


Figure 1 – Path diagram of the latent class model

Taking account of the issues aforementioned, a specific modelling framework is developed (Figure 1).

It is noted from Figure 1 that the SRD is observed and serves as an indicator or a manifest variable of the factor "general attitude" which is not observed directly. Together with some observed socio-demographic characteristics of individuals, the factor influences the formation of separate classes across which the preferences of individuals differ.

2.3 Model formulation

2.3.1 Class-specific choice model

In this study, individual n belonging to latent class s ($s = 1,...,S$) derives satisfaction from choosing alternative i in choice set C_n ($C_n = \{\text{Action, No action}\}$), and the level of satisfaction is measured by the utility $U_{in|s}$:

$$U_{in|s} = \boldsymbol{\beta}'_{is}\boldsymbol{x}_n + \varepsilon_{in} \tag{1}$$

where $\boldsymbol{x}_n$ is a vector of the features of the information displayed and socio-demographic characteristics of individual n, β'_{is} is a vector of utility parameters associated with alternative i for class s, and ε_{in} is the error term in the utility.

Under the assumption that individual n chooses an alternative that maximises his/her satisfaction, alternative i is chosen if and only if $U_{in|s} \geq U_{jn|s}$, $\forall j \neq i$, $i, j \in C_n$. Assuming the error term ε_{in} follows an IID Gumbel distribution, the probability of individual n choosing alternative *i* conditional on latent class *s* can be expressed by an MNL model (McFadden, 1974; Swait, 1994) as:

$$P_{in|s} = \frac{\exp(\mu_s \boldsymbol{\beta}'_{is} \boldsymbol{x}_n)}{\sum_{j \in C_n} \exp(\mu_s \boldsymbol{\beta}'_{js} \boldsymbol{x}_n)} \tag{2}$$

where μ_s is a non-negative scalar for latent class *s*.

2.3.2 Latent class membership model

Following Swait (1994) and Boxall and Adamowicz (2002), the latent class membership model segments all individuals into *S* classes, where the number of classes *S* is determined exogenously. As showed in the path diagram for this study (Figure 1), the membership likelihood function Y^*_{ns} for individual *n* and class *s* ($s = 1,...,S$) is unobserved and a function of the unobserved attitudes and the socio-demographic characteristics, and all the relationships between various latent constructs and observed variables can be represented as follows:

$$Y^*_{ns} = \boldsymbol{\gamma}'_{as} \boldsymbol{p}^*_{na} + \boldsymbol{\gamma}'_{zs} \boldsymbol{x}_{nz} + \zeta_{ns} \tag{3}$$

$$\boldsymbol{p}^*_{na} = \boldsymbol{\beta}'_a \boldsymbol{p}_{na} + \boldsymbol{\zeta}_{na} \tag{4}$$

where Y^*_{ns} is the likelihood membership function for individual *n* to belong to class *s*; $\boldsymbol{p}_{na}$ is the vector of attitudes of individual *n*; $\boldsymbol{x}_{nz}$ is the vector of observed socio-demographic characteristics of individual *n*; $\boldsymbol{p}_{na}$ is the vector of observed indicators of attitudes; $\boldsymbol{\gamma}'_{as}$, $\boldsymbol{\gamma}'_{zs}$ and $\boldsymbol{\beta}'_a$ are the parameter vectors; ζ_{ns} and $\boldsymbol{\zeta}_{na}$ are the error terms. Substituting the factor score equation (4) into the structure model (3), the likelihood membership function can be written as:

$$Y^*_{ns} = \boldsymbol{\lambda}'_s \boldsymbol{z}_n + \zeta_{ns} \tag{5}$$

where $\boldsymbol{z}_n$ represents both the indicators of attitudes and socio-demographic characteristics of individual *n*, that is $\boldsymbol{z}'_n = [\boldsymbol{p}'_{na}, \boldsymbol{x}'_{nz}]$; $\boldsymbol{\lambda}'_s$ is the vector of parameters to be estimated and $\lambda'_s = [\gamma'_{as}, \gamma'_{zs}]$.

As discussed by Swait (1994), individual *n* falls into class *s* if and only if $Y^*_{ns} \geq \max\{Y^*_{nj}\}$ ($j \neq s$, $j = 1,...,S$). It is assumed that the error terms ζ_{ns} s are independent across individuals and classes and are not correlated with $\boldsymbol{\zeta}_{na}$, and that the errors follow an identical Gumbel distribution with a non-negative scalar α. Then, the probability for individual *n* to belong to class *s* can be expressed by a logit function:

$$W_{ns} = \frac{\exp(\alpha \boldsymbol{\lambda}'_s \boldsymbol{z}_n)}{\sum_{k=1}^{S} \exp(\alpha \boldsymbol{\lambda}'_k \boldsymbol{z}_n)} \tag{6}$$

3.3.3 Joint model of latent class membership and action choice

Denote P_{ins} the probability for individual *n* to choose alternative *i* ($i \in C_n$) and to belong to class *s* ($s = 1,...,S$). Then P_{ins} can be calculated as:

$$P_{ins} = P_{in|s} W_{ns} \tag{7}$$

The marginal probability of individual n choosing alternative i ($i \in C_n$) is equal to the summation of the above joint probability across all classes, that is

$$P_{in} = \sum_{s=1}^{S} P_{in|s} W_{ns} = \sum_{s=1}^{S} \left(\frac{\exp(\mu_s \boldsymbol{\beta}'_{is} \boldsymbol{x}_n)}{\sum_{j \in C_n} \exp(\mu_s \boldsymbol{\beta}'_{js} \boldsymbol{x}_n)} \right) \left(\frac{\exp(\alpha \boldsymbol{\lambda}'_s \boldsymbol{z}_n)}{\sum_{k=1}^{S} \exp(\alpha \boldsymbol{\lambda}'_k \boldsymbol{z}_n)} \right) \tag{8}$$

Under the following conditions:

$$\mu_s = \mu, \ \boldsymbol{\beta}'_{is} = \boldsymbol{\beta}'_i, \ \boldsymbol{\lambda}'_s = \boldsymbol{0}, \ \forall s \tag{9}$$

the marginal probability (8) can be expressed as:

$$\begin{aligned} P_{in} &= \sum_{s=1}^{S} \left(\frac{\exp(\mu \boldsymbol{\beta}'_i \boldsymbol{x}_n)}{\sum_{j \in C_n} \exp(\mu \boldsymbol{\beta}'_j \boldsymbol{x}_n)} \right) \left(\frac{\exp(\boldsymbol{0})}{\sum_{k=1}^{S} \exp(\boldsymbol{0})} \right) \\ &= \sum_{s=1}^{S} \left(\frac{\exp(\mu \boldsymbol{\beta}'_i \boldsymbol{x}_n)}{\sum_{j \in C_n} \exp(\mu \boldsymbol{\beta}'_j \boldsymbol{x}_n)} \right) \left(\frac{1}{\sum_{k=1}^{S} 1} \right) \\ &= \frac{\exp(\mu \boldsymbol{\beta}'_i \boldsymbol{x}_n)}{\sum_{j \in C_n} \exp(\mu \boldsymbol{\beta}'_j \boldsymbol{x}_n)} \end{aligned} \tag{10}$$

and the corresponding model is an MNL. In other words, the MNL is nested inside the LCM, which makes it sensible to measure the gain, such as improvement in the likelihood ratio index, of adopting a LCM against using its MNL counterpart. The scalar and parameters μ_s and $\boldsymbol{\beta}'_{is}$ in Equation (2) and (8) are inseparable in estimation and set $\mu_s = 0$ in order to take $\boldsymbol{\beta}'_{is}$ identifiable. Similarly, α is set equal to zero in the model estimation.

3. DATA

3.1 Survey on driver responses to the RTTIS

The survey is part of investigation into driver responses to In-Vehicle Information Systems (IVIS), the other parts being drivers' behaviour in choosing departure times and travel routes. It is carried out through a SP (Stated Preference) simulator programmed on the Microsoft ASP.net framework. The generation of a subsequent choice scenario by the simulator is determined by the specific answer to the preceding question, or the set of scenarios displaced sequentially on a computer screen is automatically tailor-made for each respondent. A trip from Scarborough Beach Road to the Business School of the University of Western Australia (UWA) in Perth, Western Australia (WA) is examined.

Data collection was conducted from May to June 2009. Respondents were recruited through an information brochure distributed in the UWA, vehicle tyre/wheel workshops and municipal councils within the boundary of the proposed trip. In addition, WA governmental agencies including Main Roads and Department of Planning and Infrastructure also helped advertise the survey through their Intranets. A total of 282 effective respondents were collected from a variety of sources.

Table 1 – ANOVA analysis

Data source	Collection period	Observations	Age			Gender		
			Mean	*F* value	Sig.	Mean	*F* value	Sig.
ABS census	08/2002	36,932	35.32	0.955	0.328	0.49	0.071	0.789
Online survey	06/2009	282	35.11			0.47		

Table 2 – Variable descriptions for the latent class model

Variable	Definition
Choice	Choice decision: Action=1
Fuel saving	Fuel saving by inflating tyres: 0.8, 1.4, 2.0
Expression	Manner of information expression: 1 if “Fuel saving” expressed as “0.8, 1.4 or 2 Litres/100km”; 0 if “Fuel saving” expressed as “5, 10, or 15 %”
Extra travel time (min)	Extra travel time due to inflating tyres at a petrol station: 5, 8, 12
Fuel tank	Fuel tank level: 0 if nearly empty; 0.5 if half full; 1 if full
Suggestion	Suggestion by the RTTIS: To inflate your tyres along the route displayed on the screen=1
Trip purpose	Purpose of travel: Business travel=1
Road type	Road the respondent travels on: Freeway=1
Daily driver	Driving frequency: If drive once per day or more than once per day=1
Weekly driver	Driving frequency: If less then daily but drive once or more than once per week=1
Infrequent driver	“Daily driver” and “Weekly driver” equal 0
Female	Gender: Female=1
High school	Highest qualification: If high school=1
TAFE	Highest qualification: If TAFE (technical and further education) =1
Undergraduate	Highest qualification: If undergraduate degree=1
Postgraduate	Highest qualification: If postgraduate degree=1
Others	“High school”, “TAFE”, “Undergraduate” and “Postgraduate” equal 0
Age	Age band: 22 if <27; 32 if 28-37; 42 if 38-47; 52 if 48-57; 60 if >57
Survey duration (min)	Choice response time: recorded by the background software

In essence, these respondents are self-selected and highly motivated to participate in the online survey, which may lead to the sample being biased. Consequently, two important demographic variables age and gender, which determine the future population make-up, society and economy in a region (ABS, 2002), are used to assess the sample bias. The result of an analysis of variance (ANOVA) for the sample data and the Australian Bureau of Statistics’ population census for the relevant suburbs shows that with respect to age and gender, the sample is likely to be similar to the population (Table 1).

The part of survey associated with the RTTIS uses a set of stated preference questions that are based on D-efficient designs (Carlsson and Martinsson, 2002; Bliemer et al., 2009). The total of 16 decision scenarios is blocked into two sets, with one of nine questions and the other seven questions; 282 respondents produce a total of 2,302 records. In addition, the socio-demographic information (the driving frequency, gender, age and education qualification) is also collected. The descriptions of the variables are shown in Table 2.

3.2 Determination of the number of latent classes

The determination of the number of latent classes S is exogenous to the model parameter estimation, and based on some statistical criteria and on the practical judgement of analysts. Various criteria, including the Akaike Information Criterion (AIC), the Bayesian Information Criterion (BIC) and the Akaike likelihood ratio index ($\bar{\rho}^2$) have been used to determine this number (Bhat, 1997; Scarpa et al. 2006; Swait, 1994). Subject to some practical considerations, the idea of using either of these criteria is to find an S that produces the best goodness-of-fit for the model estimation. This study uses the Akaike likelihood ratio index defined as the following (Swait, 1994):

$$\bar{\rho}^2(S, \boldsymbol{\beta}_{is}, \lambda_s) = 1 - \frac{L(\boldsymbol{\beta}_{is}, \lambda_s \mid S) - p}{L(\mathbf{0}, \mathbf{0} \mid 1)} \tag{11}$$

where $\bar{\rho}^2(S, \boldsymbol{\beta}_{is}, \lambda_s)$ is the Akaike likelihood ratio index given an S, $L(\boldsymbol{\beta}_{is}, \lambda_s \mid S)$ is the log likelihood value at convergence, $L(\mathbf{0}, \mathbf{0} \mid 1)$ is the log likelihood value when $\boldsymbol{\beta}_{is} = \mathbf{0}$, $\boldsymbol{\lambda}_s = \mathbf{0}$ and $S = 1$ hold, and p is the number of parameters estimated.

Three latent class models are tested with the corresponding number of classes being two, three and four. As discussed before, the binary logit is a special case of the latent class model when the number of latent classes equals one, and is estimated as well. Table 3 shows relevant information used to determine the number of latent classes based on the Akaike likelihood ratio index $\bar{\rho}^2$.

It can be seen from Table 3 that against the binary logit model, the three latent class models are improved considerably with respect to the $\bar{\rho}^2$, suggesting the latent class models are superior to their logit counterparts. Though improvements in the $\bar{\rho}^2$ between the latent class models are somehow marginal as depicted by Figure 2, the increased value of $\bar{\rho}^2$ favours a large value for the number of classes. However, it is found that when the S value equals four, all parameters of some particular classes start having very large variances and become insignificant, suggesting all variables concerned are irrelevant. This phenomenon has previously been reported by other researchers, e.g., Scarpa et al. (2006). Therefore, three-class is chosen which corresponds to the largest $\bar{\rho}^2$ value without any class having all parameters insignificant.

Table 3 – Criteria for determining the number of latent classes

	Binary logit model	Latent class models		
	One class	Two classes	Three classes	Four classes
Number of observations	2,302	2,302	2,302	2,302
Number of parameters	12	27	42	57
$L(\mathbf{0},\mathbf{0}\,\vert\,1)$	-1535.460	-1535.460	-1535.460	-1535.460
$L(\boldsymbol{\beta}_{is},\lambda_s\,\vert\,S)$	-1328.115	-1157.767	-1103.499	-1056.489
AIC	1.164	1.029	0.995	0.967
BIC	1.194	1.096	1.100	1.110
$\bar{\rho}^2(S,\boldsymbol{\beta}_{is},\lambda_s)$	0.127	0.229	0.254	0.275

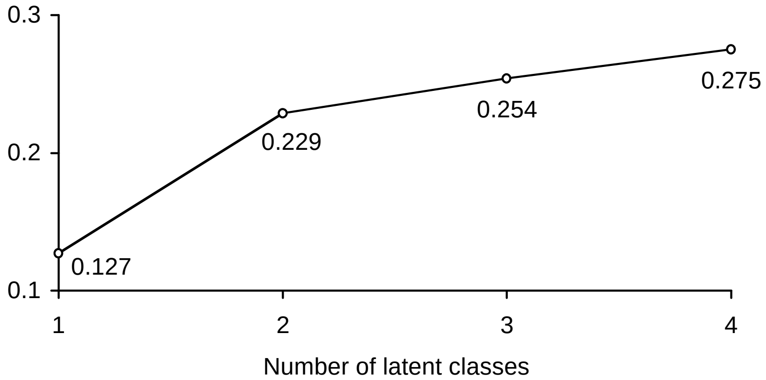


Figure 2 – Variation of likelihood ratio index with the number of latent classes

4. RESULTS AND DISCUSSION

Following the framework shown in Figure 1, several specifications with respect to choosing socio-demographic variables in the latent class models are tested. The final three-class model ends with the specification of variables as listed in Table 4. The table also presents the solution of a corresponding binary logit model for the purpose of comparison. In the latent class membership model, the parameters of the survey response duration and the gender dummy are in general significant, and accordingly the classes are identified on the basis of the two variables. A summary profile and choice probabilities of the classes are shown in Table 5.

Class 2 can be labelled “Serious respondents”, which have a larger proportion of females. On average, they spent the longest time to answer questions. This suggests that they were highly motivated and serious during the survey, taking their times to understand the questions and to make thoughtful choices about taking action.

Class 3 is titled “Rash respondents” with a majority being males. This group took the least time. It is highly likely that most individuals in this class did not spend adequate time to comprehend the questions in the questionnaire, and just chose the alternative of “No action” (77% of respondents). Considering these facts, it is likely that this group behaved as satisficers.

Class 1 can be tagged as "Pro-action respondents" with a slight majority of males. They spent reasonable time to understand the online questions, and had a tendency to choose the alternative "go to a petrol station to inflate tyres during the current trip", which is evidenced by the fact that 83% of their choices were "Action".

The parameters on the survey response duration are significant at the 5% level for the serious respondents and at the 10% level for the pro-action respondents. The kernel density estimator is used to demonstrate the distribution of the SRD for each class (Figure 3). For example, the rash respondents have a large proportion of insignificant parameters on the features of the RTTIS, implying they chose the alternative "No action" irrespective of the scenarios. A similar satisficing phenomenon has been observed in other online surveys where respondents just chose the first option of multiple alternatives irrespectively and spent the least time (Malhotra, 2008).

Table 4 – Parameter estimates

	Binary logit		Latent class					
			Class 1		Class 2		Class 3	
Parameters	Est.	Sig.	Est.	Sig.	Est.	Sig.	Est.	Sig.
Class-specific choice mode:								
Constant	2.532	0.00	8.916	0.00	2.276	0.00	-0.449	0.84
Expression	-0.397	0.01	0.237	0.55	-0.612	0.00	-1.184	0.15
Fuel saving	0.395	0.00	-0.395	0.23	1.219	0.00	0.291	0.67
Extra travel time (min)	-0.137	0.00	-0.505	0.00	-0.187	0.00	-0.163	0.10
Fuel tank	-1.022	0.00	-0.745	0.01	-2.141	0.00	1.117	0.07
Suggestion	0.048	0.65	0.090	0.72	0.033	0.82	0.088	0.83
Trip purpose	-1.140	0.00	-5.820	0.00	-1.634	0.00	4.598	0.04
Road type	0.484	0.02	1.085	0.05	0.379	0.17	2.886	0.06
Extra time x Trip purpose	0.102	0.01	0.410	0.00	0.215	0.00	-0.537	0.04
Fuel tank x Road type	-0.154	0.26	-0.570	0.15	-0.236	0.20	-1.151	0.10
Daily driver	-0.360	0.01	-0.456	0.19	-0.417	0.02	-1.852	0.00
Weekly driver	-0.186	0.25	-0.775	0.04	-0.135	0.51	-31.117	1.00
Latent class membership model:								
Constant			0.179	0.80	-0.653	0.37	0	
Survey duration			0.148	0.10	0.217	0.02	0	
Female			1.022	0.11	1.604	0.01	0	

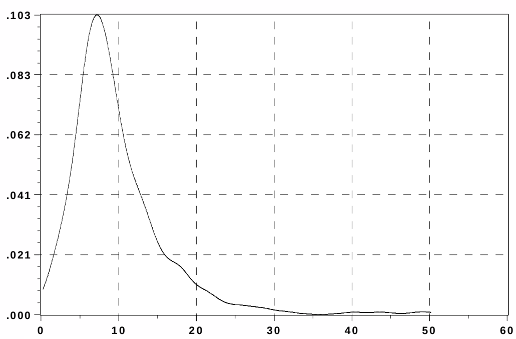
Table 5 – Characteristics of the three latent classes

	Class 1		Class 2		Class 3	
	Action	No action	Action	No action	Action	No action
Proportion of sample (%)	42%		50%		8%	
Survey duration (mean)	8.89 min		11.22 min		6.69 min	
Female (mean)	0.46		0.60		0.24	
Choices by classes (counts)	804	165	566	576	43	148
(%)	83	17	50	50	23	77

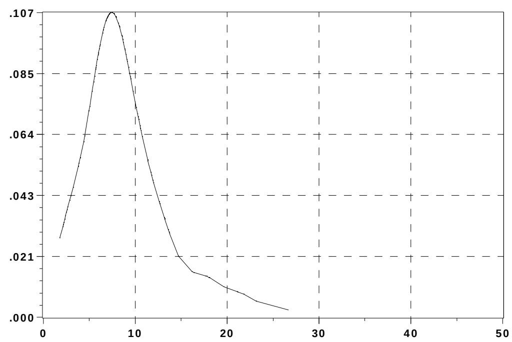
4.1 Preferences for the features of the RTTIS

The parameter on “Constant” in the binary logit model is positive and significant, suggesting that all individuals in the single class have intrinsic preferences for “Action”. The latent class discloses not only the preferences but also the preference heterogeneity across classes. Class 1 displays a very high level of intrinsic preference for “Action” probably due to their concerns on other issues that are not included in the set of features of the RTTIS in the questionnaire, such as the safety issue. The serious respondents in Class 2 have a medium level of preferences for “Action”. However, for those rash respondents, the constant is negative but insignificant. This suggests that individuals in Class 3 have some preferences for “No action” but the preferences vary considerably within the class, which is likely to be associated with their satisficing behaviours.

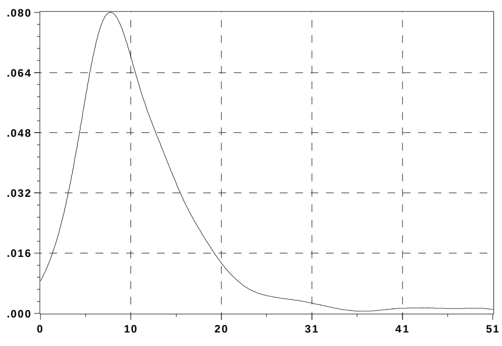
The binary logit model has a negative and significant parameter on “Expression”, and this indicates that individuals are in general likely to be influenced by the manner of expression of “Fuel saving” in “%” to inflate tyres during the current trip and the expression “Litres/100km” is less effective. Each class has quite different responses. Class 1 has a wide range of preferences across individuals within the class for the expression in “Litres/100km”, which is evidenced by the parameter on “Expression” being positive and insignificant. Class 2 has a negative and significant parameter on “Expression” and this suggests that individuals in this class have quite homogenous preferences for the condition being expressed in “%”. Though Class 3 displays a negative parameter on “Expression”, the preferences vary across individuals to a certain extent, which is suggested by the corresponding parameter being insignificant.



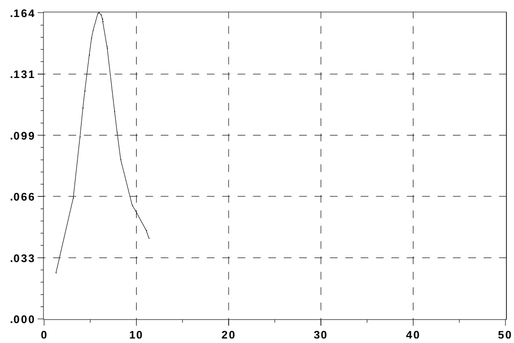
(a) Kernel density for SRD for the sample



(b) Kernel density for SRD for Class 1



(c) Kernel density for SRD for Class 2



(d) Kernel density for SRD for Class 3

Figure 3- Kernel densities for SRD

The parameter on "Fuel saving" in the binary logit model is significant and has a positive sign, which is consistent with microeconomic theories. However, the latent class model uncovers the heterogeneity of preferences across individuals. Class 1 has a negative and insignificant parameter on "Fuel saving". The negativity of the parameter contradicts the assumption of reality, and the insignificance suggests that the preferences of individuals in the pro-action class vary widely with a negative mean that is not significantly different from zero. Class 2 has a significant parameter with a sign consistent with common sense. The parameter for Class 3 is positive but insignificant, which could be a result of their satisficing behaviours that cannot have a meaningful interpretation through the parameters of the LCM.

The "Extra travel time" in both models are significant and have a negative sign. The parameter values in Classes 2 and arguably 3 of the latent class model are comparable, but the value in Class 1 is larger. In other words, individuals in Class 1 are more sensitive than those in the other classes to time.

The "Fuel tank" in the binary logit model and in Classes 1 and 2 of the latent class model are significant and the sign is consistent with the expectation that individuals are more likely to go to a petrol station when the fuel tanks of their vehicles are less full. Individuals in Class 2 are more likely than those in Class 1 to be influenced by fuel tank levels. The abnormality of Class 3, which has a significant estimate but an irrational sign, is probably a compounding of their satisficing behaviours and some odd characteristics that have not been captured in the survey.

The only preference that does not change much over models and across classes is for "Suggestion". All parameters on "Suggestion" are insignificant. The estimation results show that drivers act on the merits of the factual information and ignore the textual suggestions provided by the system. For engineering design, more effective ways of suggesting that drivers inflate tyres should be considered, e.g., a continuous warning sound and a system scoring the vehicle's operating performance.

4.2 Effects of peripheral conditions and socio-demographic characteristics

"Trip purpose", "Road type" and the driving frequency are peripheral to the RTTIS but can moderate the individuals' utilities derived from a given set of features of the information system.

The parameters on "Trip purpose" in the binary logit model and Classes 1 and 2 of the LCM are all significant and have a negative sign. This is consistent with the fact that anyone on a business trip has a time constraint and therefore is likely to avoid activities that may cause delay. The sign of the parameter in Class 3 contradicts the constrained time condition of an individual on a business trip.

The estimates on "Road type" in all models indicate that drivers tend to be more likely to inflate tyres while travelling on a freeway. This is consistent with the result that they are more concerned about safety due to high speeds on a freeway collected from the pilot survey.

Regular drivers are less likely to change their routines. This is probably because they are more experienced than infrequent drivers in operational conditions of vehicles and hence are less agitated about tyre pressures.

4.3 Summary

The latent class model not only improves the goodness-of-fit of estimation against the basic binary logit model, but also discloses the preference heterogeneity across classes of individuals. Individuals are grouped into one of the three classes based on their gender and attitudinal indicator "Survey duration", and these three classes have quite different preferences and/or attitudes. The latent class model also identifies a class that spends the least times on the survey and has a high proportion choosing "No Action" option irrespectively, which leads to that most of parameters being statistically insignificant. These facts arguably amount to satisficing behaviour. Class 2 spent most time in responding to the questions and has no intrinsic preference for the alternative "Action" or "No Action". It comprises a group of individuals whose choices are probably the most substantive. In contrast, individuals in Class 3 do not behave as a utility maximiser but a utility satisficer. This small group should be outlined and their choices can not meaningfully interpret the real behaviour with respect to the RTTIS.

5. CONCLUSIONS

This paper is designed to determine drivers' behaviour in the context of a new RTTIS, with an emphasis on the individual's sensitivity to information and the heterogeneity of the responsiveness across groups of individuals.

One of the contributions of this study is that the latent class model developed is probably one of the few models in the transport context that include attitudinal variables in identifying the latent memberships of individuals. A unique feature of the attitudinal indicator in the paper is that the corresponding response duration data is collected objectively and implicitly through the background software, which contrasts with most attitudinal indicators that are collected explicitly through attitudinal questions. This paper provides evidence to show that the use of attitudinal indicators can lead to significant differences in model results, therefore potentially affect policy decisions in formulating rules to shift new vehicle technologies towards more acceptable and effective paths over the long term.

The survey response duration has a strong explanatory power with respect to class membership, and is arguably consistent with the preference heterogeneity across classes. Since individuals in one class are identified to be satisficing, the answers by these individuals would therefore be questionable. In other words, the preferences seemingly elicited through the parameters on the corresponding variables may not be close to the real preferences.

This paper can offer some guidance for further research:

First, from the perspective of specification design for the RTTIS, it can be concluded that the majority of drivers could be triggered by the RTTIS to maintain right tyre pressures. The use of different strategies to supply information leads to significant differences in performance. For example the model results indicate that individuals act on the merits of the factual information and ignore the textual suggestions.

Second, considering that more and more studies collect data through internet-based surveys, relevant attitudinal information, such as survey duration, helps interpret the preference results. In other preference surveys for new technologies/products that are administered by interviewers, it is also important to collect attitudinal indicators, such as respondent's loyalty to certain brands and average duration to accept a new technology in the past.

Finally the latent class model in this study explores the impact of settings of the RTTIS on individuals' choices. The settings do not specifically belong to each of the choice alternatives as attributes, but are features of the information system. Though this type of model with a single class is not new (Greene, 2007; Schmidt and Strauss, 1975), the latent class model is an application of the multinomial logit model with multiple classes, which is different from those formulations with variables in utility functions being attributes of alternatives. This model can shed light on applications to investigate the impact of settings of new technologies on choice of alternatives. Furthermore user preferences for new vehicle technologies are not static. To capture the dynamics of driver perceptions and incorporate that into design policy, a hierarchical choice modelling approach is under development.

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