A LATENT CLASS APPROACH FOR MODELLING DRIVER PREFERENCES IN NEW IN-VEHICLE INFORMATION SYSTEM DESIGN

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ABSTRACT: In this paper a latent class modelling approach to capture the sensitivity and preference heterogeneity of individuals with respect to travel information is developed. Estimates for a three-class model are discussed in detail to demonstrate the potential of this approach in characterising the customer segments and preferences for an innovative vehicle technology. The results provide clear evidence of the preference heterogeneity across classes. To further illustrate applications of the model, its use in the design of a Real-Time Tyre Information System is discussed.

1 OBJECTIVE

The goal in deploying Intelligent Transport Systems (ITS) is to enhance the efficiency of transport and to improve the on-road safety of vehicles. Fulfilment of the goal needs the engagement of drivers. However, progress in understanding driver responses to some ITS applications (e.g., In-Vehicle Information System) has been far behind the pace of technology advances. This imbalance is likely to result in vehicle manufacturers and/or technology vendors prescribing ineffective specifications for ITS technologies.

In the context of the investigation of driver behaviour, the heterogeneity and susceptibility with respect to the information provided through In-Vehicle Information System (IVIS) are two important issues. The heterogeneity deals with the fact that there likely exist the segments of drivers, who respond to the same information differently. The susceptibility can be considered as a composite measurement of the magnitude to which the driver is influenced by travel information to take an appropriate action. These issues are becoming increasingly important to specify the system to link its attributes with user preferences, as well as to market a particular specification of the new vehicle technology to the right driver segment.

In this paper, the latent class model (LCM) is used to accommodate preference heterogeneity across individuals. A stated-preference survey is carried out with respect to the choice of the action under various scenarios. 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. In this work, the Real-Time Tyre Information System (RTTIS) design is used throughout the paper to explain the research motivation as well as to demonstrate the proposed approach.

The organisation of the rest of this paper is as follows. The rationale for the latent class mode and a specific framework are presented in Section 2. This is followed by a descriptive analysis of the data in Section 3. Section 4 provides details of the implementation for a new Real-Time Tyre Information System design. Final section draws conclusions.

2 METHODOLOGY

2.1 Latent Class Modelling Approach

In essence, the mixed logit model (MLM) treats the preference heterogeneity as a continuous distribution function, and the LCM can be seen as a special case of the MLM where a step function is used to approximate the continuous curve [1], with the step values being the levels of preference of a finite number of latent classes of individuals. However, it is hard to decide on the statistical ground which model (MLM or LCM) is preferable. Therefore, practical considerations need to be sought for determining a proper model: the effectiveness and the efficiency in marketing a specification of an IVIS.

If we segment the drivers into n classes, the effectiveness means that within each class drivers are statistically homogenous with respect to their preferences, whereas between classes drivers have heterogeneous preferences. The efficiency depends on the number of classes (S). The MLM produces a set of parameters or preferences that are specific to individuals and their applications to the system design would be most effective but least efficient. Though the LCM can come up with a set of parameters specific to individuals, it groups the full set into a finite number of classes, with the parameter values being equal across individuals within a class. Consequently, a LCM framework is used in this study.

The formulation of the proposed latent class model follows the general framework developed by McFadden [2], and put into operation by Swait [3]. 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. 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 membership.

As discussed later, the choice information was collected through a self-administrated web survey. 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, was implicitly collected. The SRD provides a unique chance to capture the attitude of the respondent towards a survey and a hypothetical product because it is a measure of the amount of willingness, commitment and psychological and physiological capability [4, 5].

Taking account of these issues mentioned, a specific modelling framework is developed (Figure 1). In this LC framework, the heterogeneity is accommodated in a mixture by linking a random and a deterministic approach. To allocate individuals into the different classes, a probabilistic model is used. The class formation is a function of the factor "general attitude" which is not observed directly, together with observed socio-demographic characteristics of the individuals.

2.2 Model specification

In this study, individual n belonging to latent class s ($s = 1,...,S$) derives satisfaction from choosing alternative i in choice set

$$C_n = \{\text{Action, No action}\} \quad C_n \text{ ()},$$

and the level of satisfaction is measured by the utility $U_{in|s}$:

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

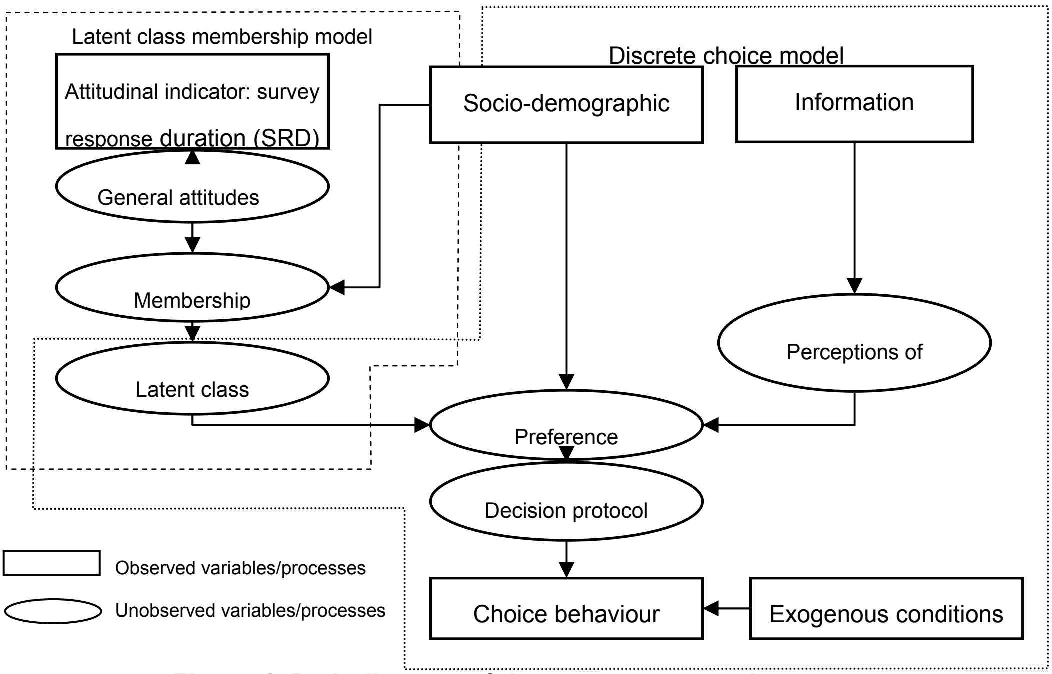


Figure.1. Path diagram of the latent class model

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 [3, 6] as

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

where μ_s is a non-negative scalar for latent class s. Following Swait [3] and Boxall and Adamowicz [7], 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 is unobserved and all the relationships between various latent constructs and observed variables can be represented as follows:

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

$$\boldsymbol{p}^*_{na} = \boldsymbol{\beta}'_a \boldsymbol{p}_{na} + \zeta_{na} \quad (4)$$

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 ζ_{na} are the error terms. Substituting the factor score equation (4) into the structure model (3), the likelihood membership function can be written as:

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

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 $\boldsymbol{\lambda}'_s = [\boldsymbol{\gamma}'_{as}, \boldsymbol{\gamma}'_{zs}]$. As discussed by Swait [3], individual n falls into class s if and only if $Y^*_{ns} \geq \max\{Y^*_{nj}\}$ ($j \neq s$, $j = 1,\ldots,S$). It is assumed that the error terms ζ_{ns}s are independent across individuals and classes and are not correlated with ζ_{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:

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

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

$$P_{in} = \frac{\exp(\mu \beta'_i \boldsymbol{x}_n)}{\sum_{j \in C_n} \exp(\mu \beta'_j \boldsymbol{x}_n)} \tag{10}$$

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 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 Background to In-Vehicle Information System Design

Given a road network during a period, the movements of vehicles are a collective consequence of decisions made individually by road users. This engagement can be regarded as a decision-making process of drivers in response to information, and be broken down into three stages: exposure, evaluation, and action. This is a complex process involving driver's psychophysical judgments, value judgments and personal decision rules [8]. Some of the decisions have macro-scope impacts on the performance of the road network, such as the choice of whether or not making a trip, departure times, destinations, travel modes and routes. The others can be classified as micro decisions and their consequences are more confined to the operating conditions of individual vehicles.

A SP (Stated Preference) survey is designed to investigate into driver responses to IVIS, the three-dimensional choices being drivers' behaviour in choosing departure times, travel routes and inflating tyres. It is carried out through an ASP.net based simulator (Figure 2). 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. 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 alternatives. These variables give the features of the information rather than the attributes of the choice alternatives.

The proposed approach can be applied to specific systems. To further illustrate application of the model, we consider its use in the design of an innovative Real-Time Tyre Information System (RTTIS). It has been recognised that proper tyre pressures contribute considerably to a vehicle's on-road safety and operating efficiency, which in turn impacts on its CO2 emissions. In the wake of tyre safety concerns, the Tyre Pressure Monitoring System (TPMS) is being made mandatory in the United States by the enactment of the TREAD Act 2000 [9,10]. The European Parliament has also proposed a regulation to make TPMS mandatory, which will take effect in 2012 [11]. However, it appears that tyre pressure maintenance has remained a low priority and a recent survey in Australia is such an example [12]. To some extent, this phenomenon can be explained by lack of prompt information on tyre pressure and the action alternatives for inflating a low-pressure tyre.

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

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

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. An analysis of variance on the survey data shows that the sample is unbiased as far as the distributions of age (below 18 years old: 1.1%; 18-27 years old: 30.4%; 28-37 years old: 35.0%; 38-47 year old: 16.6%; 48-57 year old: 11.7%; above 57 years old: 5.2%) and gender (male: 53.4%; female: 46.6%) are concerned, based on a benchmark of the census data from the Australian Bureau of Statistics [13]. The descriptions of the variables are shown in Table 1.

Table.1. Variable descriptions for the latent class model

Variable	Definition and levels
Choice	Choice decision: Action=1, No action=0
Fuel saving(litre)	Fuel saving by inflating tyres: 0.8, 1.4, 2.0
Expression	Manner of information expression: 1 if "Fuel saving" expressed as "Litres/100km"; 0 if "Fuel saving" expressed as "%"
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 to inflate 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
Female	Gender: Female=1
Survey duration (min)	Choice response time: recorded by the background software

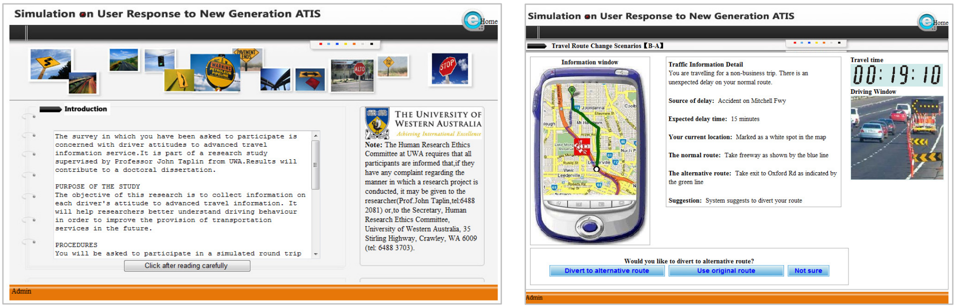


Figure.2. Screenshot examples of the simulator

Table.2. 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
$L(\mathbf{0},\mathbf{0}\mid 1)$	-1535.460	-1535.460	-1535.460	-1535.460
$L(\beta_{is},\lambda_s\mid S)$	-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
$\bar{\rho}^2(S,\beta_{is},\lambda_s)$	0.127	0.229	0.254	0.275

3.2 Model estimation

3.2.1 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 ($\overline{\rho}^2$) have been used to determine this number [14, 15, 3]. 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:

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

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

It can be seen from Table 2 that the latent class model improves the goodness-of-fit of estimation considerably against the basic binary logit model. Three-class is chosen which corresponds to the largest $\overline{\rho}^2$ value without any class having all parameters insignificant. Moreover, this S value is plausible from the perspective of the efficiency and effectiveness of marketing the RTTIS to the right customers.

3.2.2 Class profiles

The final three-class model ends with the specification of variables as listed in Table 3. A summary profile and choice probabilities of the classes are shown in Table 4.

Class 1 can be tagged as “Pro-action respondents” with a slight majority of males. They spent a reasonable amount of time in understanding the online questions, and 83% of their choices were “Action”.

Class 2 can be labelled “Serious respondents”, which have a larger proportion of females. On average, they spent the longest time in answering questions. This suggests that they were highly motivated and serious during the survey.

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, and just chose the alternative of “No action”, which constitute 77% of their choices.

3.2.3 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 "rash" attitudes.

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.

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 the rash attitudes.

The "Extra travel time" in both models are significant and have a negative sign. The parameter values in Classes 2 and 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 rash attitudes 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.

3.2.4 Effects of peripheral conditions and socio-demographic characteristics

The peripheral conditions 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 prior to the SP 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.

Table.3. Parameter estimates and significances: binary logit and 3-class LC solutions

	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.4. Three class segments: choice preference and average SRD

	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 APPLICATION IN THE CONTEXT OF A NEW RTTIS DESIGN

The Tyre Pressure Monitoring System (TPMS) is a built-in or retro-fitted device to monitor the air pressures inside tyres. The legislations in US and Europe have changed TPM from being an add-on option to being mandatory. By 2008, some car manufacturers such as AUDI, BMW and Mercedes-Benz have had all car models equipped with the TPMS. Others including Alfa-Romeo, Citröen, FIAT, Ford and Volkswagen have installed the device on some of their cars. On the other hand, manufacturers can be chiefly interested in finding the cheapest way to comply with relevant legislations and to maintain their margins, rather than to explore the full wealth of tyre information which can be gleaned.

The LC modelling approach provides informative recommendations for a new tyre information system. For example:

The display of fuel cost saving can be expressed in "litres/100 km" and/or in "dollars/100 km". Considering that drivers tend to ignore textual advices, more effective ways of suggesting that drivers inflate tyres are considered, e.g., a continuous warning sound and a system scoring the vehicle's operating performance.

The model results indicate that drivers tend to be more likely to inflate tyres while travelling on a freeway than on a non-freeway, and consequently an ancillary system is needed to encourage drivers to inflate tyres when the vehicle travels on a non-freeway.

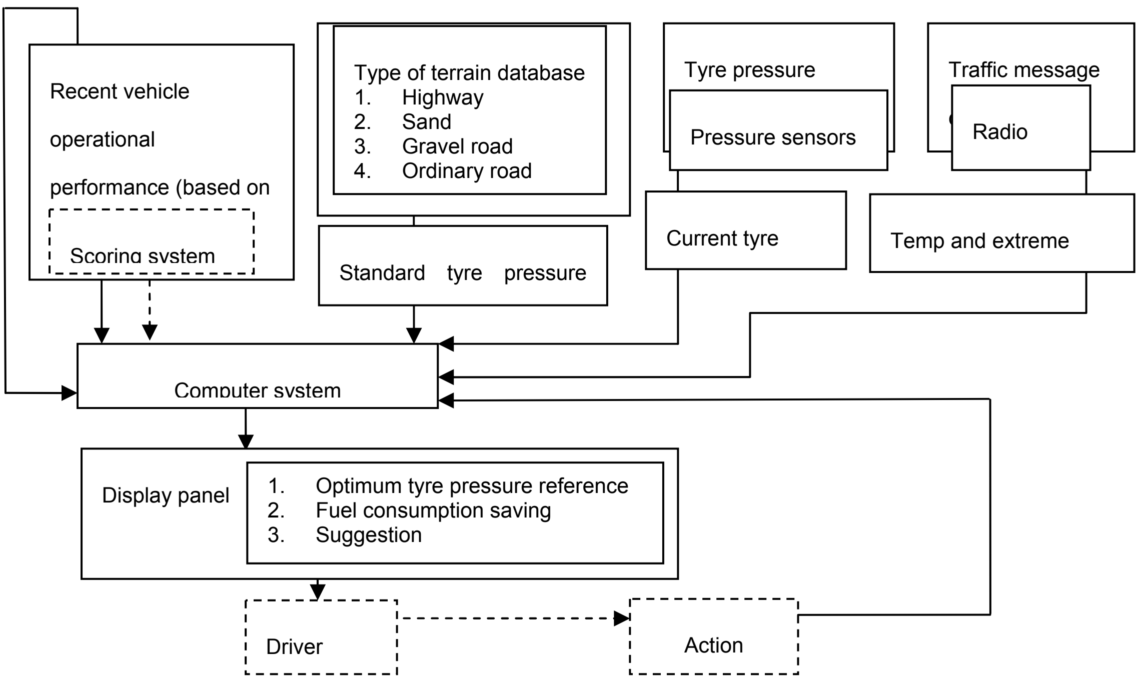
Transformation and integration of raw data into a form that matches user preferences has been found a useful design principle. For example the model results indicate that individuals act on the merits of the factual information.

Whether the system impacts all drivers equally or whether some may benefit more or conversely be at a greater risk of the distracting effect needs to be considered. Auditory rather than, or in addition to, visual display, may substantially mitigate driver distraction [e.g.16]. Considering the ergonomic theories and the respondent preferences collected through the survey, the display is designed to be a dual-mode panel.

As an extension to the TPMS, the RTTIS in this study can be divided into four major functional blocks: data collection, computing, display, and feedback (Figure 4). The GPS/GIS continuously picks up information on the terrain and the current position of the vehicle. The TMC provides real-time traffic information (such as extreme weather and congestion). The TPM sub-system integrates intelligent sensors [17], to collect a full range of valuable data generated by tyres including pressure, temperature and tyre stiffness. The on-board computer processes all these pieces of information and generates messages to be displayed. Then, the display panel shows optimum pressure references. With any deflated tyre, the RTTIS provides the position of the nearest petrol station, the extra minutes required to inflate tyres, and the estimated saving of fuel cost based on the vehicle's recent fuel consumption (e.g., the last 100 kilometres travelled) should the driver choose to inflate tyres.

Experiments are currently being done on a unit design and laboratory set-up. When this experimental system operates, it will be implemented on a few experimental vehicles.

Figure.4. Simplified block diagram of the RTTIS



5 CONCLUSIONS

The focus of this paper is on the choice modelling rather than on the engineering design. In terms of better-informed travel decisions, the alternative information content and the user interface trigger different behaviour responses. Nevertheless, implementation of the LCM approach provides a more objective and complete basis for new IVIS design than an approach based purely on technological capability or economic considerations.

This paper can offer some guidance for further research:

First, 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. 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 regulations to shift new vehicle technologies towards more acceptable and effective paths over the long term.

Second, considering that more and more studies collect data through internet-based surveys, relevant attitudinal information, such as the survey duration, helps interpretation of 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 [18, 19], 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.

6 ACKNOWLEDGEMENTS

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