EVALUATING THE EFFECTS OF MULTI-MODAL TRAVEL INFORMATION BASED ON THE PRINCIPLE OF RELATIVE UTILITY MAXIMIZATION

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Abstract

It's well known that information plays a significant role in influencing individual travel decisions, however, ITS deployment becomes slow these days. To provide additional evidence that the provision of information is effective in promoting modal shift, this paper attempts to establish a new nested choice model based on the principle of relative utility maximization (called r_NL model), in order to properly evaluate the effects of multi-modal travel information, which is expected to encourage the use of transit systems and consequently to mitigate traffic congestion. The principle of relative utility maximization assumes that an individual chooses an alternative with the highest relative utility considering his/her relative interests in alternatives from choice set. The new model can be used to represent unequal, asymmetric and heterogeneous choice structures of decision-makers under the influence of incomplete information and context dependence. The effectiveness of the r_NL model was empirically confirmed by using a stated preference data collected in Japan. It turns out that the provision of multi-modal travel information can increase the users of a reliable transit system by 7-11%, reduce the car users by 3-5% and also leads to the decrease of bus users by 4-6%.

Keywords: Multi-modal travel information; Principle of relative utility maximization; r_NL model; Stated preference survey; Heterogeneity
Topic Area: B1 Public Transport and Intermodality

1. Introduction

Governments around the world are seeking to tackle the ever-rising levels of urban transportation issues such as traffic congestion and air pollution, mainly caused by the rapid progress of high car-dependent modern society. On the other hand, the advanced information technology provides not only unlimited business opportunities for entrepreneurs to develop and sell IT products and services (Golob, 2001), but also open up new ways to solve the contemporary transportation issues. Accordingly, transportation research community is becoming increasingly sensitive to impacts of IT on travel (Golob, 2001, Golob and Regan, 2001). Information plays a significant role in influencing individual travel decisions. This has been investigated in several contexts including route guidance, provision of transit information, and highway congestion and incident related information (Vaughn *et al.*, 1999). Due to the rapid progress of information technology, nowadays, travelers can easily access real-time travel information through various media such as Internet, mobile phone and cable TV on one hand, and further increase of information users becomes slow on the other (Peirce and Lappin, 2004).

Kenyon and Lyons (2003) classify travel information into three categories: 1) uni-modal travel information, 2) multi-modal travel information, and 3) integrated multi-modal travel information. Uni-modal travel information may integrate information about a number of operators, but it is limited to providing information about a single mode. As argued by Kenyon and Lyons, seeking information about a number of travel modes using uni-modal travel information not only requires time-consuming consultation with a number of different information sources but also prior knowledge of these sources, plus the desire to both travel by and to seek information about a non-habitual travel mode. In contrast, multi-modal travel information provides information about more than one mode of travel at a single point of access to multiple sources of information. This makes information about the available modes more accessible and, consequently reduces the effort associated with the search for information. Integrated multi-modal travel information automatically presents the users with information concerning different modes in response to a particular journey specified by the users, and minimizes the users' effort in acquiring information on mode choice even if they had not intended to consider or review a mode choice decision when accessing the service.

Multi-modal travel information seems to be able to encourage car users switching to the usage of transit systems under congested traffic situations. However, as argued by Abdel-Aty (2001), although many previous studies have investigated the effect of information on drivers' behavior and route and departure time choices, few studies have attempted to explore the potential of information on transit ridership. One can find many studies on both technical delivery and accessibility of travel information (Adler and Blue, 1998; White, 2000), and on the development of information contents, both marketing and enabling in nature, which is relevant to user needs (Gillam, 1999; Kenyon *et al*, 2000; Lyons, 2001; Mehndiratta *et al*., 1999; INFOPOLIS, 1999). However, there is little evidence to suggest that the provision of information has been effective in promoting modal shift (Kenyon and Lyons, 2003; Lappin, 2000).

It has been argued that there exists a number of cognitive barriers which must be overcome before users to choose the information to make decisions on mode choice: 1) the decision to consider an alternative mode, 2) desire to use an alternative mode, 3) seeking information about information sources, and 4) using and compiling information about the viability of a variety of modes (Kenyon and Lyons, 2003). Kenyon and Lyons examined the potential influence of integrated multi-modal travel information on modal change based on a qualitative approach, called focus group survey method with small-scale samples. In contrast, this paper develops a new modeling framework that can simultaneously incorporate the influence of the aforementioned four barriers and quantitatively evaluate the effects of multi-modal travel information on modal change, by using a stated preference (SP) survey method. To represent individual choice behavior, this paper adopts the principle of relative utility maximization, which assumes that an individual chooses an alternative with the highest relative utility considering his/her relative interests in alternatives from choice set (Zhang *et al.*, 2004). It aims at not only showing additional evidence about the effectiveness of information in promoting modal shift, but also providing behavioral hints for better design of intelligent travel information systems, which is considered very important to deploy ITS technologies (Adler and Blue, 1998). The target travel information is pre-trip information, which is assumed accessible at home.

2. Discussions on methodological issues

Like many behaviors routinely performed in every day life, travel mode decisions are supposed to be often made in a rather 'mindless', automatic fashion (Banister, 1978; Goodwin, 1977; Verplanken *et al*, 1994). In other words, travel behavior is often habitual

(Arentze and Timmermansm, 2003; Bamberg *et al*, 2003; Fujii and Kitamura, 2003; Gärling and Axhausen, 2003; Garvill *et al.*, 2003; Schlich and Axhausen, 2003). By examining the role of habit in information processing underlying daily travel mode choices, Aarts *et al.* (1997) found that habit reduced the elaborateness of information use in judgments of travel mode use. This suggests that analysis of the effects of travel information provision cannot ignore this kind of habitual decision-making mechanism.

On the other hand, because of incomplete information, choice history, interest and/or trip purposes, individuals usually sort out some of information sources and travel modes, and consequently do not recognize each alternative equally. Furthermore, choice behavior is dependent on status quo or reference point(s) and it is empirically confirmed that change of reference point might lead to preference reversal (Tversky and Kahneman, 1991). This implies that individuals may asymmetrically evaluate different alternatives because of the influence of their present chosen alternatives and/or the initial state(s) of choice decision-making. Accordingly, it is realistic to assume that individuals may show an unequal and asymmetrical evaluation structure for different alternatives in the choice process.

In addition, choice behavior is a complex decision making process and highly adaptive to the demands of the task (Payne, 1976). Therefore, no single heuristic does well across all tasks and context conditions (Payne *et al.*, 1988). When the complexity (defined by the number of alternatives, number of attributes, correlation between attributes etc.) in choice tasks increases, decision makers attempt to adapt their choice behavior to their limited ability and attempt to reduce the information-processing load. As a result, decision makers usually use simple, local and myopic choice strategies (Olshavsky, 1979; Payne *et al.*, 1988, 1993; De Palma et al., 1994). This observation has given rise to information-processing theories of choice, which are dominant in the behavioral sciences. In addition, due to the heterogeneous influence of information-accessing experiences and the attitude on information reliability, individuals may show selective behavior about information sources and contents, and consequently may not refer to all of the given information. It is also pointed out that decision makers will choose the strategy to delay choice, seek new alternatives, or even revert to status quo option when the choice environment is made complex (Dhar, 1997a, b).

The above-mentioned matters suggest that method of evaluating the effects of multi-modal travel information should reflect these behavioral mechanisms. This paper will develop a new choice model based on the principle of relative utility maximization. The new model will represent not only the nested choice structure of travel mode choice and information acquisition behavior, but also incorporate the influence of selective behavior about information sources and contents.

3. Reviews of relevant discrete choice models

Over the last two decades, discrete choice models have proven to be very powerful tools for policy development and evaluation in transportation research. Since the late 1970s, the development of choice models has focused on methodological challenge to relax the Independence of Irrelevant Alternatives (IIA) property characterizing the widely used multinomial logit (MNL) model in many disciplines. In transportation research, the interest in developing non-IIA models seems to have faded slightly as a result of the emerging field of activity-based models of travel demand, but recently a renewed interest is visible (Zhang *et al*, 2004). The majority of non-IIA models introduced in the transportation research literature avoid the IIA property by allowing for covariances between the error terms of the utility functions for all or bundles of choice alternatives. Although these models are computationally tractable and may result in intuitively better predictions of traveler choice behavior, a shortcoming of these non-IIA models is that the parameters for these covariances often are difficult to interpret in behavioral terms.

Timmermans and Golledge (1990) classified the existing non-IIA choice models into three categories. The first group of non-IIA models avoids the IIA property by relaxing the assumption of identically and independently distributed error terms, or allowing for different variances of error terms, or allowing for positive correlations between error terms, or allowing for both. The second group of non-IIA models circumvents the IIA property by extending the utility specification to account explicitly for similarity between choice alternatives. In other words, the models argue that individual choice behavior is context-dependent. The third group of non-IIA models assumes a hierarchical or sequential decision-making process.

Models belonging to the first category differ in terms of their assumptions regarding the type of distribution of the error terms (extreme value distribution, normal distribution, negative exponential distribution) and the assumptions on the error terms ((in)dependently and/or (not) identically or general variance-covariance structure and taste variation). In general, increasing the error variance of a choice alternative implies that the probability of choosing that alternative increases, even if the deterministic term of the utility function is equal to that of other alternatives. Likewise, the effect of introducing covariances between the error terms of two alternatives is that they draw more shares from each other. The relevant models include multinomial probit (MNP) model (Bolduc, 1999; Daganzo, 1979; Liu and Mahmassani, 2000; Yai *et al.*, 1997), heteroscedastic extreme value (HEV) model (Bhat, 1995), mixed logit and probit model (Revelt and Train, 1998; Brownstone and Train, 1999 and Brownstone et al., 2000), McFadden's (1978) GEV model.

The non-IIA models belonging to the second category share the property that substitution/similarity effects (i.e. context dependence) are incorporated by explicit consideration of the degree of similarity between the choice alternatives. The importance of context dependence in the choice models has been recognized since the 1960s (Rushton, 1969). There exists no unified and widely acknowledged definition about the context dependence in the sense that it is described differently in different disciplines. Zhang *et al.* (2004) made an initial attempt to unify the definition and classify the context dependence into three categories: (1) alternative-specific context, (2) circumstantial context and (3) individual-specific context. The alternative-specific context includes the number of alternatives and their attributes, the correlated structure of attributes and the availability of alternatives. The background context defined by Oppewal and Timmermans (1991) belongs to the circumstantial context. This context can also include the status quo of choice over a population. The individual-specific context refers to the individuals' choice history, household or workplace attributes, and the cognitive status quo of the reference group such as the car ownership of their neighbors and acquaintances. In general, context-dependent choice models can be classified into two categories: one assumes utility maximization and another does not. The former includes the mother (or universal) logit model (McFadden *et al.*, 1977; Anderson *et al.*, 1992, Timmermans *et al.*, 1996), the dogit model (Gaudry and Dagenais, 1979; Hensher and Johnson, 1981), context-sensitive model of spatial choice behavior (Borgers and Timmermans, 1988) and Miyamoto *et al.*'s (2004) discrete choice model with structuralized spatial effects. Considering that Miyamoto *et al.*'s model represents both the observed and unobserved spatial effects, it also belongs to the first categories of choice models. The latter includes the reference- and context- dependent models (Kahneman *et al.*, 1991; Tversky and Kahneman, 1991; Simonson and Tversky, 1992; Tversky and Simonson, 1993) and the models based on Kahneman and Tversky's (1979) prospect theory.

The best-known model with a hierarchical decision structure is the NL model, which is a special case of McFadden's GEV model. Recently, other types of such models have also been derived from McFadden's GEV model, including PCL model (Koppelman and Wen, 2000), NPCL model (Fujiwara *et al.*, 2000), CNL model (Vovsha, 1997; Papola, 2000), OGEV model (Small, 1987), PD model (Bresnahan *et al.*, 1997) and GNL model (Wen and Koppelman, 2001), and GenL model (Swait, 2001). A completely different approach is Tversky's (1972) EBA model.

All the models described in this section assume that choice behavior is compensatory. These models allow a low score on some attribute to be at least partially compensated by high scores of one or more remaining attributes. In contrast, non-compensatory models assume that individuals screen choice alternatives on an attribute-by-attribute basis when arriving at a choice or decision (Timmermans and Golledge, 1990). Since this paper only treats compensatory models, the non-compensatory models developed recently are not further reviewed here.

4. Modeling framework for multi-modal travel information

To represent the above-mentioned behavior mechanisms systematically, the principle of relative utility maximization (Zhang *et al.*, 2004) is applied here. The concept of relative utility has its roots in the research about income, which argues that individuals tend to compare themselves to others in deciding their income levels (Duesenberry, 1949; van de Stadt *et al.*, 1985). The relative utility assumes that utility is meaningful only relative to some reference point(s), and acknowledges the fact that individual choice behavior is context-dependent. Leaving the detailed explanations about relative utility to Zhang *et al.* (2004), an operational relative utility function is summarized as follows:

$$U_{ij} = r_{ij} \sum_{j' \neq j} \left(v_{ij} - v_{ij'} \right) + e_{ij} \qquad (1)$$

$$0 \leq r_{ij} \leq 1 \;\; and \; \sum_j r_{ij} = 1 \qquad (2)$$

where

U_{ij} is the relative utility of individual *i* choose alternative *j*,

v_{ij} is a latent variable explaining the influence of observed information of alternative *j*,

r_{ij} is relative interest (importance) parameter for alternative *j*, and

e_{ij} is an error term.

One can see that relative utility function is defined as the sum of all the differences of conventional utilities between each pair of the alternative in question and all other alternatives in choice set. The concept of relative interest stems from multiple-issue group decision-making theory (Coleman, 1973; Gupta, 1989), which argues that actors involved in negotiations are usually more interested in one issue than in another. Extending this concept to the context of travelers' choice behavior, it can be stated that travelers are usually more interested in one alternative (e.g. travel mode) than in another, or travelers may regard some alternatives more important than others. If the relative interest parameter is defined as a function (equation (3)) of individual attributes and behavioral factors (x_{ijs} with parameter θ_{js}), it can represent the heterogeneous choice structure across individuals.

$$r_{ij_0} = \frac{1}{1+\sum_{j\neq j_0} exp(\sum_s \theta_{js} x_{ijs})}, r_{ij} = \frac{exp(\sum_s \theta_{js} x_{ijs})}{1+\sum_{j\neq j_0} exp(\sum_s \theta_{js} x_{ijs})} \tag{3}$$

where j_0 is a reference alternative. One can assume any alternative as a reference one in estimating the relevant parameters.

If it is further assumed that error term e_{ij} in equation (1) follows an independent and identical Weibull distribution with respect to all alternatives and individuals, the following choice model (called r_MNL model) can be obtained.

$$P_{ij} = \frac{exp\{ r_{ij} \sum_{j'\neq j}(v_{ij} - v_{j'})\}}{\sum_k exp\{ r_k \sum_{k'\neq k}(v_{ik} - v_{ik'})\}} \tag{4}$$

If relative interest parameter r_{ij} is equal across alternatives, the r-MNL model collapses into the conventional MNL model.

Extending the equation (1) to the case of nested choice issue results in a new nested choice model (called r_NL model).

$$P_{i,dm} = P_{i,m|d} \cdot P_{i,d} \tag{5}$$

$$P_{i,m|d} = \frac{exp\left(r_{im} \sum_{m'\neq m}\left((v_{im} + v_{imd}) - (v_{im'} + v_{im'd})\right)\right)}{\sum_{m'} \left\{exp\left(r_{m'} \sum_{m''\neq m'}\left((v_{im'} + v_{im'd}) - (v_{im''} + v_{im''d})\right)\right)\right\}} \tag{6}$$

$$P_{i,d} = \frac{exp\left(\lambda r_{id} \sum_{d'\neq d}\left((v_{id} + v'_{id}) - (v_{id'} + v'_{id'})\right)\right)}{\sum_{d'} \left\{exp\left(\lambda r_{id'} \sum_{d''\neq d'}\left((v_{id'} + v'_{id'}) - (v_{id''} + v'_{id''})\right)\right)\right\}} \tag{7}$$

$$v_{id} = ln\left(\sum_m exp\left(r_{im} \sum_{m'\neq m}\left((v_{im} + v_{imd}) - (v_{im'} + v_{im'd})\right)\right)\right) \text{ and } 0 < \lambda \leq 1 \tag{8}$$

where λ is parameter of inclusive value v_{id}.

Considering the nested choice structure for travel mode and information acquisition, here, the r_NL model will be applied. The r_NL model can not only provide an operational approach solving the methodological issues mentioned in section 2, but also represent the interdependence among alternatives in the same choice nest, which is ignored in the conventional NL model.

5. Data

5.1 Selection of survey area and respondents

To investigate the influence of multi-modal travel information on modal shift (especially from cars to transit systems), it is necessary to select the respondents who are not captive car users, i.e., who usually selectively use both cars and transit systems for their daily trips. To meet this requirement, a residential area located in the northwestern part of Hiroshima City was selected. The area is about 10km far from the city center. Currently, the available travel modes are cars, buses and a LRT (called Astramline, opened before the 12th Asian Game in 1994). The direct buses to the city center were withdrawn after the opening of Astramline, and became available again since March 2002. However, even after the opening of Astramline, traffic congestion during the rush hours is still serious. On the other hand, it is difficult to cut the prices of transit systems. Accordingly, it becomes more and more important to introduce travel demand management measures to tackle the traffic congestion, especially under such serious time of economic recession.

Two pilot surveys were conducted in 1999, to properly select the respondents. The first pilot survey was done to select the respondents who were not captive car users, and the second to understand the needs for travel information. In the first pilot survey, 9,555 questionnaires were handed out, and 2,384 were collected. It is shown that among the respondents, 35% (1,210) are captive car users, 37% (1,174) use the Astramline and the remaining 28% (924) are the current car users who answered to use transit systems if the level of service would be improved. The second pilot survey was done to the 2,098 (=1,174+924) respondents who are not captive car users, among which 1,866 answered to willingly participate in the further survey. Consequently, 998 respondents answered the questionnaires. It is confirmed that for the trip at the designated day, 523 took the Astramline and 475 used the cars. In addition, 287 out of 523 Astramline users have available cars for him/herself. Finally, 762 (475 car users plus 287 Astramline users having available cars) were selected as the potential users of multi-modal travel information in this study.

5.2 Summary of survey results

The survey was conducted in 2002 and consists of a revealed preference (RP) survey and a SP survey. In the RP survey, individual attributes, attitude of information acquisition and current travel choice behavior was investigated. The individual attributes include age, gender, ownership of information devices (PC, mobile phone and cable TV) and information-accessing experience etc. The attitude data are about travel mode comparison, pre-trip information search, and active access to information, access to multiple information sources, dynamic travel information and predicted travel information. Current travel choice behavior refers to trip frequency, travel time and cost by mode to the city center etc.

In the SP survey, respondents were asked to answer several hypothetical choice questions about information acquisition and travel mode with respect to commuting and shopping purposes. The assumed choice alternatives are information acquisition devices (personal computer, mobile phone and cable TV), intention of information acquisition (yes or no) and travel modes (car, bus and Astramline). Travel information includes length of road traffic congestion shown either in print or diagrammatically, timetables for bus and Astramline, and total travel time for all the travel modes. For each travel mode, either no information is given or only one type of information is available. The level-of-service variables include only travel time for car and bus, and length of car traffic congestion. Travel time for Astramline was fixed. Since this study examines the effects of travel information under different conditions of traffic congestion, other level-of-service variables like travel cost were ignored for the sake of reducing respondents' burden in answering SP questions. To reflect individuals' selective behaviors about information contents, respondents were asked to report their referred information content(s) during the choice process. Based on SP design method, 25 profiles were obtained (for the detailed explanation, see Zhang and Fujiwara, 2004). To reduce the respondents' burden, the 25 profiles were grouped into 5 balanced blocks. Each respondent received only one block of 5 profiles. As a result, 681 questionnaires were handed out and 565 were successful collected with the high response rate of 83%.

Based on the RP survey results, it is found that 64%, 49% and 37% of the respondents own personal computers, mobile phones and cable TVs, respectively. To access various information, 49% of respondents use the Internet via personal computers and 36% use the mobile phones. It is shown in the SP survey that only 42% of respondents reported to refer to all the given information. In other words, more than half of the respondents selectively consulted the information.

6. Model estimations and analysis of information effects

6.1 Alternative model structures

The SP survey included three alternatives for travel modes (car, bus and Astramline), two alternatives for information acquisition (Yes or No), and three alternatives for information devices (PC, mobile phone and cable TV). If joint choice structure is assumed, the total number of target alternatives is 18 ($3 \times 2 \times 3$). In case of nested choice structure, three choice levels need to be considered (see Figure 1). To examine which type of model structure is the most suitable to represent the choice behavior observed in the SP survey, four models are estimated, i.e., MNL and r_MNL models for the joint model structure, and NL and r_NL models for the nested model structure, respectively.

6.2 Representing cognitive barriers in the models

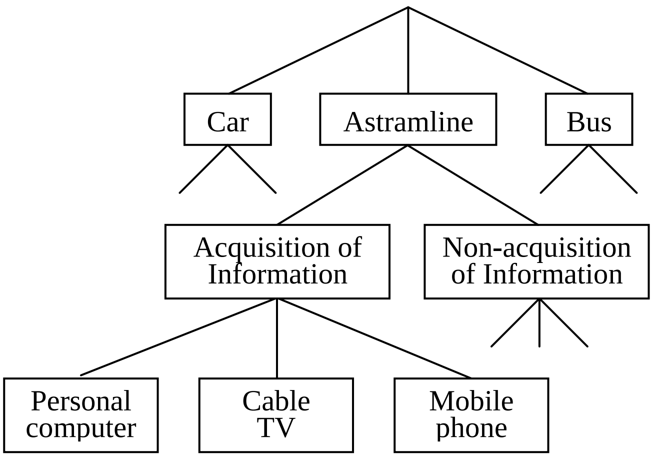


Figure 1. Nested Choice Model Structure under Multi-modal Travel Information Provision

As argued by Kenyon and Lyons (2003), there are four major cognitive barriers, which must be overcome before the users to choose the information for the decision-making about a travel mode choice. This forces the analysts to properly represent these four cognitive barriers when evaluating the effects of multi-modal travel information.

The first cognitive barrier: decision to consider an alternative mode

Since the survey respondents were selected from trip-makers who are not captive car users, it can be said that all of the respondents in this study take the alternative mode(s) into account when attempting to choose the target mode. However, it is not clear how and to what extent the respondents do. Then modeling approach is required to represent this point. Since relative utility is defined as the sum of all the differences of latent variables between the target alternative and other alternatives in choice set (see equation (1)), it is obvious that the model structure based on equation (1) is first representing the way of individual decision to consider alternative mode(s). On the other hand, the relative interest parameter is assumed to differ across alternatives. This means that the influence of alternative *j'* on the choice of alternative *j* is indicated by $-r_{ij}$ and that of alternative *j* on alternative *j'* is by $-r_{ij'}$. If one further re-write equation (1) as,

$$U_{ij} = r_{ij} \sum_{j' \neq j} \left(v_{ij} - w_{ijj'} v_{ij'} \right) + e_{ij} \tag{9}$$

where $w_{ijj'}$ indicates the weight of the influence of alternative *j'* on the choice of alternative *j* in question.

Then $-r_{ij} w_{ijj'}$ can be used to represent the influence of alternative *j'* on alternative *j*, and the influence of alternative *j* on the choice of alternative *j'* becomes $-r_{ij'} w_{ij'j}$. Zhang and Fujiwara (2004) developed a quasi-nested choice model (called r_QNL model) based on equation (9) and empirically confirmed its effectiveness by using the same SP data in this study. Here, to simplify the discussions of the proposed r_NL model, it is assumed that $w_{ijj'} = 1$.

The second cognitive barrier: Desire to use an alternative mode

This cognitive barrier usually needs to be specified by applying the attitudinal survey method. In this study, this can be comprehensively incorporated into the model by using the concept of relative interest, since the relative interest determines the relative importance of each alternative making for individuals' utility in the choice process. The desire to use an alternative mode will be influenced by not only the habitual decision-making about mode choice (Gärling and Axhausen, 2003), but also the attitude for the decision-making about travel mode. The information about habitual decision-making and attitude for mode choice is available in the RP survey.

The third and fourth cognitive barriers

"Seeking information about information sources" and "using/compiling information about the viability of a variety of modes" is directly related to the preference of information acquisition and the choices of information devices here. The relevant information is also collected in the RP survey. In fact, the second, third and fourth cognitive barriers are inseparable from each other, especially focusing on the attitude variables. These variables included in the RP survey are, the attitudes about travel mode comparison, pre-trip information search, active access to information, access to multiple information sources, dynamic travel information and predicted travel information.

6.3 Explanatory variables

Since the aforementioned attitude variables influence not only information acquisition, but also travel mode choice, it is proposed here to estimate a common latent variable "attitude for information acquisition". The estimation results are shown in Figure 2. It is obvious that the model shows a high goodness-of-fit index (GFI and AGFI). All the parameters are statistically significant and have expected positive signs. Positive parameters suggest that people are willing to compare different travel modes and actively consider the use of alternative mode(s), and make use of information for travel decisions. Comparing the magnitude of each parameter, it seems that there exist higher barriers in travel mode comparison (*the first and second barriers*) and pre-trip information search (*the third barrier*) than *the fourth barrier*. Positive and significant parameter of attitude for travel mode comparison explicitly supports the assumption made in equation (1). The calculated latent variable "attitude for information acquisition" will be used to explain the information acquisition behavior later.

In addition, all of the variables included in the SP survey are introduced into the models. Since more than half of respondents selectively referred to the travel information, for each assumed information content, a dummy variable is defined to indicate if the target information is available and if the respondent refers to that information during the choice process. Several other variables including age, current trip frequency by mode to the city center, and experience of using information devices are selected from the RP survey based on a preliminary analysis to explain the relative interest parameters. Current trip frequency and experience of using information devices are used to represent the influence of habitual decisions.

6.4 Model accuracy

The estimation results for each model using the above-mentioned explanatory variables are shown in Tables 1 and 2. Focusing on the model accuracy (i.e., adjusted McFadden's Rho-squared), it is obvious that the r_MNL model accuracy is 23% higher than that of the MNL model, and the r_NL is 7% higher than the NL model. This first suggests that introducing the concept of relative utility can improve the model performance. For the joint choice model structure, there are 18 alternatives, which are composed of different travel modes and information-related alternatives. It is not difficult to expect that there exist high similarity among alternatives. The similarity among alternatives, one type of context dependence, cannot be properly represented in the MNL model due to its IIA property (Zhang *et al.*, 2004). From equation (1), one can easily observe that the closer the observed attributes among alternatives, the smaller the values of relative utilities. In other words, the higher the observed similarity among alternatives, the lower the choice probability. This finding is clearly intuitive. On the other hand, comparing with the NL model, 7% improvement in the r_NL model accuracy also sufficiently support the conclusion that the similarity among alternatives in the nested choice structure can be satisfactorily represented by using the concept of relative utility.

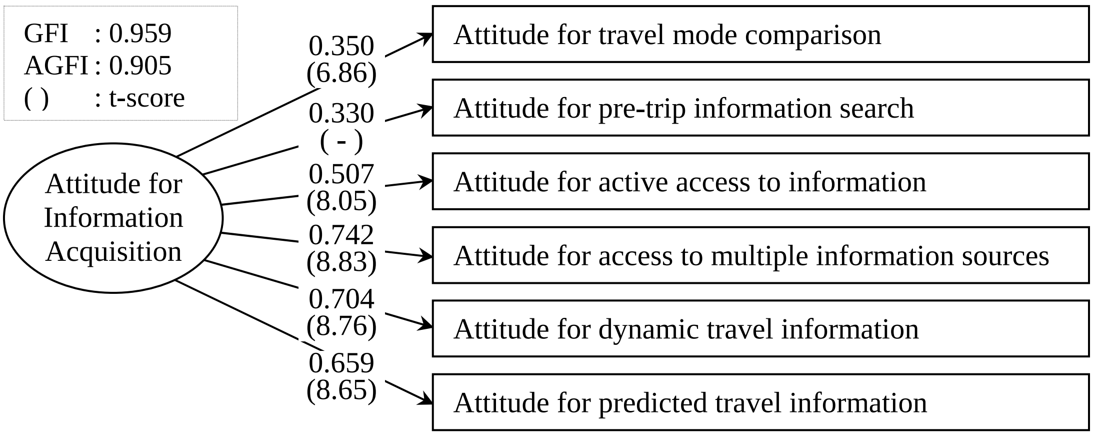


Figure 2. Estimation of Attitude for Information Acquisition

Focusing only on the model accuracy, it seems that the effect of introducing a nested model structure is larger than that of the relative utility. However, it does not mean that one can ignore the behavioral mechanisms represented by the relative utility, especially from the perspective of model accountability. For the nested model structure, the parameters of inclusive values are all statistically significant and different from both 0 and 1.

Even though all the estimated parameters have logical signs and most of the parameters are significant in the MNL, r_MNL and NL models, since the r_NL model has the highest goodness-of-fit index, its estimation results will be further discussed below.

Table 1. Estimation Results of Joint Choice Model (MNL and r_MNL Models)

Explanatory variable			MNL			r-MNL		
			Parameter		t-score	Parameter		t-score
Variable related to travel mode choice								
Level of service by travel mode								
		Travel time (min.)	-0.0539	**	-15.48	-0.0382	**	-14.13
		Length of traffic congestion (km)	-0.1660	**	-4.05	-0.1546	**	-5.20
Dummy variable indicating if information content is available and referred to in the choice process (Yes 1, No 0)								
	Car information:	Total travel time	2.1954	**	14.09	1.7941	**	15.63
		Length of traffic congestion shown in print	0.7474	**	4.82	0.6971	**	6.44
		Length of traffic congestion shown diagrammatically	1.0198	**	7.01	0.8967	**	8.66
	Astramline information	Time table	2.2545	**	15.36	1.8493	**	17.14
		Total travel time	2.0447	**	14.77	1.7205	**	16.87
	Bus information:	Time table	1.5697	**	6.89	0.5846	**	2.87
		Total travel time	1.0077	**	3.95	0.0015		0.06
Variable related to information acquisition: Experience of accessing travel information using information device								
Personal computer		(Yes 1, No 0)	0.0575		0.48	0.5756	**	2.69
Mobile phone		(Yes 1, No 0)	0.8595	**	8.01	1.5721	**	8.17
Variable related to choice of information device: Ownership of information device								
Personal computer		(Yes 1, No 0)	1.0459	**	13.93	0.5686	**	8.98
Mobile phone		(Yes 1, No 0)	1.7297	**	22.48	0.8920	**	14.66
Cable TV		(Yes 1, No 0)	1.7573	**	20.55	0.8687	**	13.11
Variable for relative interest parameter								
Travel mode:		Car frequency (times/month)				0.0414	**	5.09
		Astramline frequency (times/month)				0.0222	**	3.70
		Bus frequency (times/month)				-0.3254	*	-2.02
Information device:		Age for personal computer				-0.0159	**	-4.17
		Age for mobile phone				-0.0132	**	-3.46
		Age for cable TV				-0.0129	**	-3.37
Information acquisition:								
	Yes	Attitude for information acquisition				0.1118	**	2.80
	No	Attitude for information acquisition				-0.1433	**	-2.98
Initial logarithm likelihood			-5642.006			-5642.006		
Converged logarithm likelihood			-4636.356			-4404.780		
Adjusted McFadden's Rho-squared			0.178			0.219		
Sample			1952			1952		

*: significant at the level of 95%, **: significant at the level of 99%

6.5 Behavioral implications of relative interest parameter

Statistically significant parameters of explanatory variables for interest parameters support the assumption that the interests in the choices of different alternatives are not the same and also heterogeneous across individuals. On average (see Figure 5), individuals have largest interest (its parameter is 0.56) in the Astramline, the second largest interest (its parameter is 0.24) in the car, and the smallest interest (its parameter is 0.20) in the bus. Individuals show almost the same high interests in cable TV and personal computer (their parameters are 0.50 and 0.43, respectively), however, the lowest interest (its parameter is 0.07) in mobile phone. Considering that 49% of the respondents have mobile phones, the low interest in mobile phone implies that there might exist a higher cognitive barrier in accessing travel information via mobile phone, which is usually expected as the most convenient way to access information. This should be further examined in the future by considering, for example, the influence of information-accessing cost.

Table 2. Estimation Results of Nested Choice Model (NL and r_NL Models)

Explanatory variable	NL			r-NL		
	Parameter		t-score	Parameter		t-score
Choice of travel mode						
Travel time (min.)	-0.0259	**	-8.97	-0.0248	**	-9.85
Length of traffic congestion (km)	-0.2773	**	-9.84	-0.1668	**	-5.94
Inclusive value	0.0688			0.1226		
Null hypothesis: parameter =0		**	7.55		**	7.63
Null hypothesis: parameter =1		**	102.20		**	54.60
Variable for relative interest parameter						
Astramline frequency (times/month)				0.8617	**	6.91
Bus frequency (times/month)				-0.9708		-1.69
Choice of information device						
Personal computer ownership (Yes 1, No 0)	0.9152	**	11.54	1.0409	**	14.70
Mobile phone ownership (Yes 1, No 0)	1.8323	**	21.37	2.3620	**	12.75
Cable TV ownership (Yes 1, No 0)	1.8976	**	19.68	1.7464	**	19.65
Variable for relative interest parameter						
Experience of using information devices (Yes 1, No 0)				0.6176	**	2.82
Age for personal computer				-0.0091	**	-2.77
Age for mobile phone				-0.0445	**	-4.92
Information acquisition (1 if information content is available and referred to, 0 otherwise)						
Car: Total travel time	17.4192	**	4.18	4.8464	**	5.30
Length of traffic congestion shown in print	17.6772	**	4.25	8.1910	**	4.25
Length of traffic congestion shown diagrammatically	18.4153	**	4.80	8.9530	**	4.91
Astramline: Time table	15.2586	**	4.09	11.4973	**	5.40
Total travel time	16.4690	**	4.37	9.6999	**	5.11
Bus: Time table	2.8240	**	2.92	2.7739	**	3.09
Total travel time	5.2259		1.70	1.2548	*	2.01
Inclusive value	0.0716			0.1229		
Null hypothesis: parameter =0		**	7.48		**	7.60
Null hypothesis: parameter =1		**	96.99		**	53.88
Variable for relative interest parameter						
Latent variable of attitude for information acquisition				0.3186	**	2.74
Initial logarithm likelihood	-5642.006			-5642.006		
Converged logarithm likelihood	-3943.383			-3823.120		
Adjusted McFadden's Rho-squared	0.301			0.322		
Sample	1952			1952		

*: significant at the level of 95%, **: significant at the level of 99%

Focusing on the existence of heterogeneity, experiences of using information devices have a positive influence and age has a negative influence on the choice of information devices, respectively. This suggests that the young people and the people who have experiences of accessing information devices are more likely to attach much importance to the choice of information device. Positive parameter for the latent variable attitude for information acquisition suggests that people strongly rely on travel information (interest parameter is 0.87) during the choice of travel mode. It is also shown that, the higher the frequency of using the Astramline, the larger its interest parameter. However, bus trip frequency works in an opposite direction.

Figure 5 shows unequal and asymmetric choice structures for travel modes and information devices. For example, the influence of Astramline on car choice is -0.24 while that of car on Astramline is –0.56, the influence of mobile phone on personal computer is –0.43 while that of personal computer on mobile phone is –0.07. In this sense, it can be expected to further improve the model performance by introducing equation (9) into the current r_NL model. This is left as s future research issue.

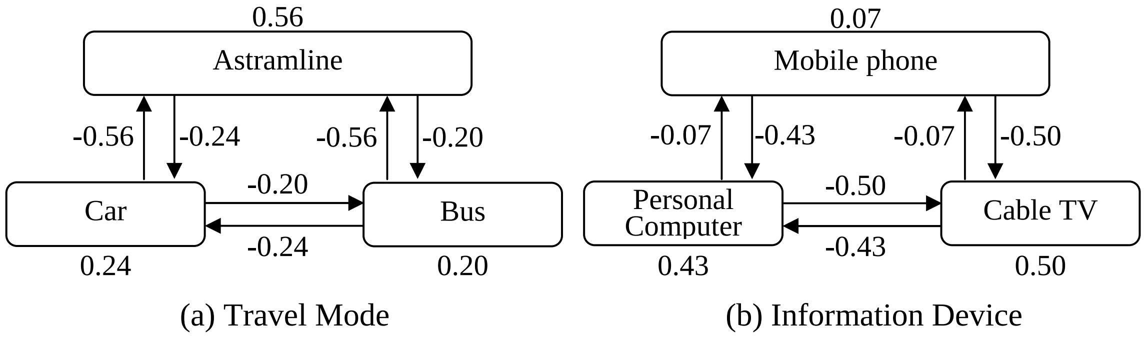


Figure 5. The Estimated Unequal and Asymmetric Choice Structures

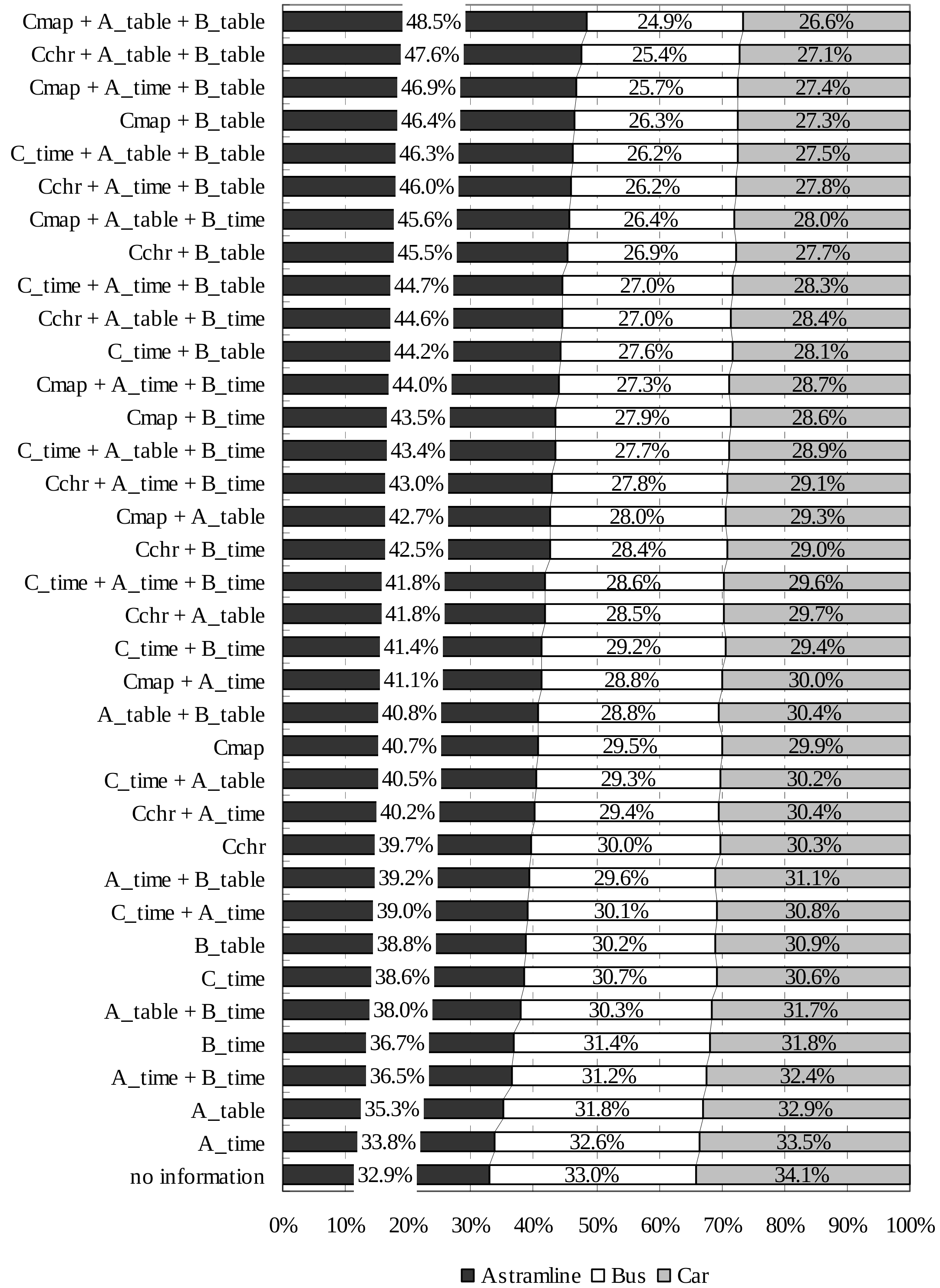
6.6 Analysis of effects of multi-modal travel information provision

All the parameters related to information contents are positive and statistically significant. This means that, 1) provision of travel information contributes to the increase in the utility of travel mode, and 2) multi-modal travel information is more effective than single-modal information. The most influential travel information is related to Astramline, followed by car. In contrast, the NL model shows the opposite results. All of the four models estimate that bus information has the lowest influence on the choices of travel modes and information acquisition behavior.

Simulation analysis is done to evaluate the influence of information on modal shift. Since at most only one type of information is available for each travel mode in the SP survey, totally 36 scenarios are assumed. The choice probability was calculated by assuming other variables are fixed at the average values. Figures 6 and 7 show the variations in modal shares due to travel information provision, where the former is related to information contents and the latter is to the number of the referred information. The findings from the simulation analysis can be summarized as follows:

1) Multi-modal travel information, which consists of traffic congestion shown diagrammatically for car and timetables for Astramline and bus, has the highest promotional effect on modal shift. In other words, one can expect the highest increase (15.6%=48.5%-32.9%) in the Astramline share, and the highest decrease (7.5%=34.1-26.6%) in the car share. It can be interpreted that information provision tends to steer people's use of more reliable travel mode, i.e., Astramline in this study. However, the bus share is also found to have the largest reduction (8.1%=33.0-24.9%).

2) For uni-modal travel information, the Astramline information has the lowest influence on modal shift. This observation is consistent with the intuition, because Astramline has the highest punctuality among the assumed three travel modes. In contrast, modal shares are largely affected by car traffic congestion information.



Note: A: Astramline, B: Bus, C: Car, time: travel time, table: time table,
Cchr : length of traffic congestion shown in print,
Cmap : length of traffic congestion shown diagrammatically.

Figure 6. Variations in Modal Shares due to Information Contents

3) The second best way to reduce car traffic is to provide users with the "dynamic" traffic congestion information shown diagrammatically and the "static" bus timetable, if the number of information contents is restricted.

4) Focusing on the influence of the number of the referred information (Figure 7), the provision of multi-modal travel information can increase the number of Astramline users by 7-11%, but reduce the car users by 3-5% and bus by 4-6%, respectively.

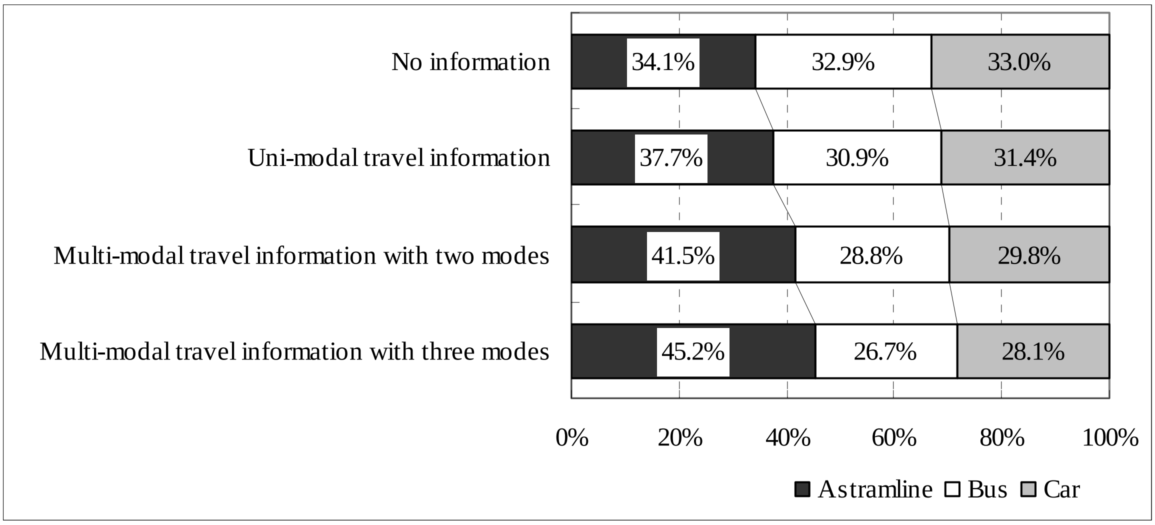


Figure 7. Variations in Modal Shares due to the Number of the Referred Information

7. Conclusions and future research issues

It seems that ITS deployment, especially in developed countries, becomes slow these days. More evidences are still needed to suggest that the provision of information is effective in encouraging the use of reliable transit systems and consequently reducing car traffic congestion. At the same time, it is necessary to effectively provide users with the really needed information. On the other hand, policy makers are also required to not only further promote information provision but also to make doing-nothing or abandonment decisions. To support these decisions, it becomes more and more important to develop sophisticated modeling and survey approaches to represent complex decision-making mechanisms under the provision of information.

Under such circumstances, this paper attempts to establish a new nested choice model (called r_NL model) for properly evaluating the effects of multi-modal travel information provision on modal shift. The r_NL model is built based on the principle of relative utility maximization. The relative utility can avoid the IIA property of the conventional MNL model based on the observed information about the alternatives in choice set. As a result, the observed similarity among alternatives can be effectively captured in the model. The r_NL model can explicitly represent the similarity among the alternatives in the same choice level, which is ignored in the NL model. Furthermore, the concept of relative interest is introduced to represent individual unequal and asymmetric choice structure, which is expected to remarkably take effect under the provision of multi-modal travel information.

As an empirical analysis, the r_NL model is applied to describe the decisions about travel mode choice and information acquisition behavior. The established model can be used to incorporate the influence of a number of cognitive barriers, which must be overcome before the users to choose the information to make decisions on mode choice. Model estimations based on the SP data collected in Japan confirmed the effectiveness of the r_NL model in describing the choice issues under the multi-modal travel information provision. It is also shown that provision of multi-modal travel information is effective in encouraging the use of a reliable transit system and mitigating car traffic congestion.

Multi-modal travel information gives an opportunity to relatively assess the related travel modes and to expand choice set even if the traveler is a "car captive". The proposed modeling approach still needs to be refined. It is also worth examining relationship between information provision and choice set formation. Due to rapid development of information technology, nowadays, people can access information almost at any time and at any place. This brings about the change in the way of decision-making about travel decisions. For example, how to make full use of information in supporting effective and smart scheduling decisions seems a promising research subject. In addition, choice behavior over time under complex decision-making environments should be examined.

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