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Mode choice models' ability to express intention to change travel behaviour considering non-compensatory rules and latent variables

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ABSTRACT

Disaggregate behaviour choice models have been improved in many aspects, but they are rarely evaluated from the viewpoint of their ability to express intention to change travel behaviour. This study compared various models, including objective and latent models and compensatory and non-compensatory decision-making models. Latent models contain latent factors calculated using the LISREL (linear structural relations) model. Non-compensatory models are based on a lexicographic-semiorder heuristic. This paper proposes 'probability increment' and 'joint probability increment' as indicators for evaluating the ability of these models to express intention to change travel behaviour. The application to commuting travel data in the Chukyo metropolitan area in Japan showed that the appropriate non-compensatory and latent models outperform other models.

1. Introduction

Disaggregate behaviour models have been applied to travel behaviour analysis, such as travel behaviour prediction, but very few attempts have been made to analyse intention to change travel behaviour itself. Since any aggregate change in travel demand must be the result of individual intention to change travel behaviour, analysing intention to change travel behaviour is very important when applying disaggregate behaviour models to forecasting.

After the theoretical background and estimation methods based on random utility theory were developed [1], disaggregate behaviour models became widely applied. Since then, these models have been improved [2]. The improvements include relaxation of the assumption concerning error components [3], choice set generation [4], and so on. Whilst the models used today are wide-ranging, in the most basic and most frequently applied framework for disaggregate behaviour models, the explanatory variables include only objective characteristics, such as travel time and travel cost, and the decision-making rule is compensatory, with utility expressed as the summation of weighted attribute values.

However, models based on this framework are problematic. Models using only objective characteristics as explanatory variables have difficulty with attributes that are not easily quantified, and an individual's taste heterogeneity is difficult to express. Moreover, the compensatory decision-making rule assumes that each individual evaluates all attribute values of all alternatives. Individuals have limited data processing capability, however, and so apply much simpler decision-making rules [5].

In addition, these models are evaluated based on the fit to the data used for the estimation (usually cross-sectional data for a single time point) even when they are applied to forecasting. In other words, models with a better fit explain the correlations amongst variables used for the estimation. However, these correlations do not always remain true over time, so a fit with the estimation data set does not necessarily correspond to a fit with data related to intention to change travel behaviour [6]. Accordingly, researchers need a suitable methodology for evaluating intention to change travel behaviour.

This study examined models suitable for explaining intention to change travel behaviour. Specifically, the authors compared models with objective characteristics only and models with latent variables only, as well as compensatory and non-compensatory models. In this paper, the authors evaluated the models using their proposed indicators for intention to change travel behaviour.

Section 2 of this paper summarises the improvements made to disaggregate choice models related to this study and also summarises the drawbacks of conventional indicators for evaluating model fit. Section 3 describes the data used in this study. Section 4 describes the disaggregate models compared in this study. Section 5 proposes indicators for evaluating the ability of these models to express intention to

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change travel behaviour. Section 6 shows estimations and compares models using the indicators proposed in Section 5. Section 7 summarises the outcomes and identifies areas requiring further research.

2. Improvements to disaggregate choice models and drawbacks of conventional indicators for evaluating model fit

2.1. Improvements to disaggregate choice models

Disaggregate behaviour models have been improved in many aspects, and the models used today are wide-ranging. This subsection discusses some of the improvements that relate to this study.

2.1.1. Latent factors of individuals

For models in which all of the explanatory variables are objective characteristics, it is difficult to include as explanatory variables any factors that are not easily quantified. The influence of factors that are not included as explanatory variables can be attributed to alternative-specific constants and/or error components. These constants, which include various unobservable factors, may not be transferrable [7]. Therefore, as many factors as possible, even those difficult to quantify, should be included as explanatory variables.

Moreover, in models using only objective explanatory variables (sometimes called objective models), an individual's taste heterogeneity is expressed only by socio-economic characteristics. An individual's socio-economic characteristics, however, such as gender and age, cannot always express that individual's taste heterogeneity. Therefore, in the field of marketing science, the individual's taste heterogeneity is tried to be clarified by analysing the unobservable components that are present in the decision-maker's inner self.

The same discussion has occurred in the field of transport research [8]. The model fit is reportedly improved by including psychometric data, such as the satisfaction level obtained from a questionnaire [9]. Predicting future psychometric data is difficult, and developing a model that can be applied to future predictions using psychometric data is expected.

Consequently, Morikawa [10] introduced latent variables that explain the factors of an individual's inner self. Morikawa used the LISREL (linear structural relations) model [11] to express the relationships between the latent variables and the other observable variables, which made forecasting possible. Research into using psychometric data continues, and the model fit reportedly has been improved by adopting both objective characteristics and latent variables as explanatory variables [12].

2.1.2. Non-compensatory decision-making rule

Human beings have a non-compensatory aspect to their decision-making [5]. However, compensatory decision-making rules, such as the linear utility function, are widely used in disaggregate behaviour modelling, mainly because compensatory decision-making rules have more handleability. The linear utility function also makes the model and its benefits easier to interpret and evaluate, suggesting the merits of compensatory decision-making rules. Individuals have limited data processing capability, however, so much simpler non-compensatory decision-making rules can be applied to actual situations. Therefore, the models should duplicate the decision-making rules actually used. A summary of non-compensatory rules can also be found in Kurauchi and Morikawa [13].

2.2. Drawbacks of conventional indicators for evaluating model fit

When cross-sectional data for a single time point is applied to a model, the indicators frequently used for evaluating model fit are ρ^2, adjusted ρ^2, AIC (Akaike's information criterion), and so on. However, these conventional indicators consider only the data used by the model and not the model's ability to express intention to change travel behaviour.

Data for intention to change travel behaviour can be obtained from SP (stated preference) surveys, which include hypothetical situations that might change travel behaviour. Accordingly, including both RP (revealed preference) and SP data in the models can be useful. However, most models are evaluated based on the model's fit to the RP and SP data [14,15]. Hence, the model fits for the RP and SP data of a specific individual are evaluated independently and do not consider the individual's intention to change travel behaviour.

When cross-sectional data for two time points are available, researchers can use the earlier time-point data and then evaluate the hit ratio and the share of predictions with the later time-point data. Or, the researchers can use the later time-point data and then evaluate the model fit to the earlier data. However, cross-sectional data at two time points do not reveal the behaviour change of a specific individual, and the model does not consider the individual's intention to change travel behaviour.

Evaluations of models that use panel data generally consider the model fit to each individual's two time-points data independently [16] or the model fit to the latter time-point data aggregately [17]. Accordingly, this evaluation does not consider each individual's intention to change travel behaviour. A detailed review of behavioural changes can be found in Kitamura [18].

3. Data

The data used in this study were obtained from the “Transport Questionnaire Survey in Commuting to Work” in cooperation with a small-scale person-trip survey (household travel survey) conducted in 1997 [19]. This survey asks questions that are not included in the conventional person-trip survey, such as travel costs, detailed information on transfers, subjective evaluations of the level-of-service of each transport mode, and so on. For example, a subjective evaluation of travel time is obtained by asking “What is your impression of the travel time?” and having respondents choose a response from the provided list (1: short, …, 5: long). Other subjective evaluation items relate to travel cost; parking, delay, and congestion of car travel; access and egress, changes, crowdedness, headway, and punctuality of public transport, and so on.

The data includes RP (current transport mode for commuting) and SP data. In the SP survey, those who commute by car but have an intention to use the bus or rail instead are asked to choose their reasons from the provided list (up to three reasons, for example, ‘if the nearest bus stop or station becomes closer to your house’) and the change in the level-of-service from the provided list (for example, a walking time of 3, 5, 8, 10, or 20 min from home to the bus stop or station) for them to choose bus or rail. Other reasons from which respondents chose relate to improvement of public transport in headway, travel time, changes, fare, punctuality, crowdedness, and so on, and to deterioration of car travel in travel time, petrol price, parking, and so on. Note that those who currently commute by bus or rail do not answer SP questions. The survey covered approximately 6000 commuters.

4. Principles of modelling

The general modelling framework is depicted in Figs. 1 and 2. Fig. 1 shows the relationships between conventional disaggregate behaviour models and the two ideas of improvements considered in this study. In the conventional model, *preference* (usually called *utility* in the field of microeconomics) is explained by objective variables such as *LOS* (*level-of-service*) *of alternatives* and *SE* (*socio-economic characteristics*) *of individuals*. The decision-making rule is usually the *compensatory rule* where decision-makers consider all attribute levels of all alternatives. The preference then explains the RP data.

Two ideas for improvements are to (a) incorporate the *latent factors of individuals* at the stage in which the objective variables explain the preference, and (b) incorporate a *non-compensatory rule* at the stage