COVARIATES OF A LATENT CLASS MODEL OF HEURISTIC ACTIVITY-TRAVEL SCHEDULING CHOICES UNDER MULTIPLE SOURCES OF UNCERTAINTY AND TRAVEL INFORMATION

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ABSTRACT

Current activity-based models of transport demand do not take uncertainty into account. It is a theoretical limitation when these models are used for short-term transport management. Travellers have to make their activity-travel choices in the context of multiple unexpected events and adjust their original plans accordingly during the implementation of their activity-travel plans. Moreover, information provision may be relevant in this context as well. Most previous research on travel information has either dealt with the importance of travel information in reducing uncertainty and the corresponding willingness to pay or with the effects of travel information on simple, mostly uni-dimensional travel choices. This work is motivated by the belief that only by considering this increased complexity ultimately dynamic activity-based models that also take travel information, route choice and activity rescheduling behaviour into account can be developed. To that end, a latent class model has been formulated which captures travellers' heterogeneity in terms of their attitudes towards uncertain events. Heterogeneity is represented by the different heuristics applied by travellers. In this sequel, membership of the latent classes and therefore decision styles is estimated as a function of household characteristics. To estimate the model, an interactive-web based travel simulator was developed. Two aspects will be discussed in this paper: decision model that utilizes decision style heuristics and covariate variable latent class model extension that includes household socio-demographic characteristics. Next, data collection

will be described in detail. This is followed by a discussion of the estimation results. Conclusion and possible avenues of future research will complete the paper.

Keywords: Route choice, uncertainty, activity-travel rescheduling, decision styles, risk attitudes

INTRODUCTION

Travel information impact has been on the focus of considerable transportation research in recent years. A key underlying assumption in this research is that information is provided to reduce uncertainty faced by the travellers. Travellers are not always clear about existing alternatives, nor are they sure about the outcomes of some uncertain events in the transportation environment, mainly unforeseeable incidents, queues and congestion and, these uncertainties are probabilistic in nature. This key assumption implies that the conceptual frameworks and theories that underlie activity-based models of travel demand are ill-suited to address this problem of short-term adjustment of planned activity-travel schedules because these models do not explicitly consider uncertainty.

Over the last couple of years, the number of studies on travel information and uncertainty has increased dramatically. Researchers have explored the relevance of various theoretical frameworks, including classical expected utility theory (e.g. Gao *et al.*, 2008; Polak *et al.*, 2008), accumulative prospect theory (e.g. Senbil and Kitamura, 2004; Avineri and Bovy, 2008) and regret theory (Chorus *et al.*, 2008). Empirical research has been largely confined to relatively simple problems, mainly related to travel time uncertainty in a particular link of the transportation network (Zhu *et al.*, 2008) about short term decisions.

The study reported in this paper is based on a series of previous works with extensions mainly to include socio-demographic variables as covariate variables for better segmenting the population. Information use and reduction of uncertainty are conceptualised not only in their own right but also in terms of their impact on activity-travel rescheduling decisions. In this regard, our model integrates work on (travel time) uncertainty (e.g. Srinivasan and Mahmassani, 2003) and activity rescheduling decisions (Mohammadian and Doherty, 2005; Bladel *et al.*, 2006; Joh *et al.*, 2006; Nijland *et al.*, 2006, , 2007; Roorda and Andre, 2007). Further, this model explicitly recognizes heterogeneity in heuristics that travellers use to cope with uncertainty and takes socio-demographic information into account.

More specifically, this paper reports the main findings of the estimation of a covariate variable latent class model, which acknowledges different risk attitudes among travellers and recognizes covariate effects of socio-demographic profiles of subjects. The estimation is based on data collected in an interactive computer experiment. Respondents were first told a storyline and then asked to take a series of rescheduling and information acquisition decisions (or to execute the original schedule and not to acquire any information) under an experimentally varied set of uncertain conditions.

The paper is organised as follows. First, we will summarize the conceptual framework underlying the study and develop the various risk attitudes and decision heuristics. Next, we will introduce the formulated covariate variable latent class model and its estimation method. Then we will briefly describe a web-based interactive computer experiment, including the specific tasks that respondents completed. This will be followed by a discussion of the model estimation results. The paper is completed with a summary, discussion of future research directions.

MODEL

The proposed model bases its decision model on the theoretical framework proposed in Arentze and Timmermans (Arentze and Timmermans, 2003; Arentze *et al.*, 2004). Before introducing the model we, therefore, first briefly summarize the relevant components of this framework.

Decision model

The basic framework assumes that activity-travel (re)scheduling decisions, if any, are made at every node in the transportation network and when an activity has been completed. Nodes in the network are important decision points because nodes allow travellers to change their route. Similarly, the completion of each activity is an important decision point in the sense that travellers can check whether the elapsed time requires them to change one or more facets of the planned activity-travel schedule. These decisions take place under conditions of uncertainty about the outcomes of events (travel times, congestion, unexpected events, availability of products in a store, etc) that are relevant for the utilities of different schedule decision options. The terms 'event' and 'outcome' here refer to any uncertain state of the system that is relevant for a scheduling decision. Because activity-travel decisions involve a sequence of routes and activities, the uncertainty is related to multiple events.

In dealing with this uncertainty, we assume that an individual develops scenarios: that is, a mental simulation of possible future states of the system that he may experience. A scenario thus defines a possible outcome and a probability representing the individual's belief of how likely it is that the scenario will be true. Let Y refer to the (uncertain) event, y_i refer to a possible outcome and $P^t(y_i)$ denote the individual's belief that $Y = y_i$ at decision moment *t*. Assume that an individual generates a (optimal) schedule for each possible scenario. Let S_{it} refer to the schedule that is optimally adapted to outcome y_i. At the moment of decision making, the individual is still uncertain about what the true outcome will be and, hence, to evaluate the schedule alternative, he has to take into account all possible other outcomes as well. Therefore, for each main variant S_i^t, a heuristic is applied to generate another set of schedules representing sub-variants. Let ($S_i^t \mid y_j$) refer to the sub-variant that is first optimized for outcome y_i and next adapted would it turn out that y_j is the true state. In case of a rational traveller, the expected utility of each schedule main variant is defined by:

$$EU(S_i^t) = \sum_j U(S_i^t \mid y_j) P^t(y_j) \quad (1)$$

where t is the decision moment, $U(\bullet)$ is the utility derived from a schedule, S_i^t is the main schedule variant, ($S_i^t \mid y_j$) the sub-variant and $P^t(y_j)$ the perceived probability of y_j. The expected utility of the best choice at decision moment t then is defined as:

$$EU^t = \max_i \left\{ \sum_j U(S_i^t \mid y_j) P^t(y_j) \right\} \tag{2}$$

To reduce uncertainty, an individual may also acquire travel information. The value of a piece of information is conceptualized as the extent to which having the information improves the decision. Assume that individuals hold beliefs about the credibility of a given information source. Let Y' denote the message received. The perception of credibility of information regarding event Y is represented by conditional probabilities of the form $P^t(Y' \mid Y)$ where $Y = \{y_1, y_2, ..., y_n\}$ are the possible outcomes for the event and $Y' = \{y_1', y_2', ..., y_n'\}$ are messages about outcomes possibly conveyed by the information source. Obviously, before receiving the information, the individual does not know the content of the message. Taking a-priori beliefs about possible messages into account, the expected utility of a decision situation before having received a message can be derived as:

$$EU^{t+} = \sum_k P^t(y_k') \max_i \left\{ \sum_j U(S_i^t \mid y_j) P^t(y_j \mid y_k') \right\} \tag{3}$$

The conditional probabilities $P^t(y_j \mid y_k')$ are derived from $P^t(y_k' \mid y_j)$ by backward reasoning (using Bayes theorem). The individual's prior belief, $P^t(y_k')$, of receiving message y_k is derived from his prior beliefs $P^t(Y)$ and conditional probabilities $P^t(y_k' \mid y_j)$. The expected value of information is then modelled as the increase in expected utility of the decision situation with information compared to the same decision situation without information, i.e. $EU^{t+} - EU^t$.

The generalization of the theory to multiple uncertain events case is straightforward if we redefine scenarios as unique outcome configurations of multiple events, i.e. $Y = Y_1 \times Y_2 \times ... \times Y_r$.

Decision tree representation

Equations (2) and (3), which define the expected utility of a decision situation without and with information, represent a conceptual model of (re)scheduling decisions in general. To operationalize the framework for the types of situations considered in the experiment, it is allowed and helpful to decompose the choice of a schedule into a sequence of decisions with uncertain outcomes and represent it as a decision tree. In a decision tree, each node in the tree structure is either a nature/chance node or a decision node. A nature node is a node that has uncertain outcomes whilst a decision node has its decision alternatives/options as several possible states. Notation $\{H\}$ is used to represent a node in general in a decision tree, H is a list representing the path from the root to the current node. Then $\{H,i\}$ denotes a node at the next level to node $\{H\}$, that is, the i-th child of $\{H\}$. Given the decision tree representation, the utility at node $\{H\}$ expected by a decision maker can be expressed as follows. If node $\{H\}$ is a nature node:

$$v_{\{H\}} = v^0_{\{H\}} + \sum_i p_{\{H,i\}} v_{\{H,i\}} \tag{4}$$

and if node $\{H\}$ is a decision node:

$$v_{\{H\}} = v^0_{\{H\}} + r \max_i \left(v_{\{H,i\}} \right) \tag{5}$$

where $p_{\{H,i\}}$ denotes the probability of the i-th outcome at node $\{H\}$ of the tree, $v_{\{H,i\}}$ denotes the utility associated to the i-th outcome of $\{H\}$, $v^0_{\{H\}}$ denotes the base utility of the state represented by node $\{H\}$ itself and r is a future discount factor (r = [0,1]). These general utility functions allow the individual to evaluate the expected utility at each node in a given tree under uncertain situations.

One way of reducing the uncertainty is to acquire information. As described above, upon acquiring information, individuals update their perception of the uncertain event so that their updated perceptions more closely reflect the true state of that event (given that the source has a positive credibility). In our model, options to acquire information are treated not different from other choices. Thus, from a decision maker's point of view, besides one decision tree consists of activity-travel decisions, he/she has to evaluate another decision tree representing information acquisition effects, that is, the same tree structure but with updated probabilities for each uncertain event, based on the information he/she got and the perceived credibility of the information. That is to say, the message an individual will get is itself an uncertain event with possible messages as the possible outcomes and probabilities determined by a-priori beliefs. Expected information value then becomes the difference in expected utility at the root node between these two decision trees.
Thus, if node $\{H\}$ is a node representing information acquisition, it has the same form as equation (5), whereby the base utility is specified as:

$$v^0_{\{H\}} = \beta_{infoprice} C \tag{7}$$

where $\beta_{infoprice}$ is a price parameter and C is the price for acquiring one piece of information from source referred to by node $\{H\}$. The sum term on the RHS of equation (5) then represents the perceived expected value of information.

Risk attitude represented by heuristics

This basic conceptual framework can be extended by introducing different risk attitudes. Different heuristics can be introduced to allow modelling different decision styles under multiple uncertain events. Three types of risk attitudes will be distinguished, namely, risk avoiders, risk takers and risk neutral individuals. They are defined here as follows. In uncertain situations, a risk avoider consistently uses the worst case scenario to make decisions – i.e. evaluates decision alternatives always under the worst outcome, a risk taker evaluates decision alternatives under most likely outcomes (i.e., ignoring probabilities of other less likely outcomes) and a risk neutral individual uses expected utility to evaluate his/her alternatives and their associated outcomes. Apart from being influenced by personal traits, the decision style chosen may vary in different situations as well for example depending on the amount of risk involved. The decision styles can be represented in the decision tree model as follows. Let C denote the total number of classes representing decision styles. Then, equation (5) can be extended as follows:

$$v_{\{H\}|c} = v^0_{\{H\}} + v^1_{\{H\}|c} \tag{8}$$

where *c* is an indicator of class membership (*c* = 1 is risk avoider, *c* = 2 is risk taker and *c* = 3 is risk neutral traveller). In this equation, the utility v^1 is defined class dependent as follows:

$$v^1_{\{H\}|1} = \min_i (v_{\{H,i\}}) \tag{9}$$

$$v^1_{\{H\}|2} = v_{\{H,k\}} \qquad k = \arg\max_i (p_{\{H,i\}}) \tag{10}$$

$$v^1_{\{H\}|3} = \sum_i p_{\{H,i\}} v_{\{H,i\}} \tag{11}$$

Latent class choice model

Using Random Utility theory, we specify the utility of each type of decision alternatives in the decision tree depending on whether it has uncertain outcomes or is followed by a next decision as follows. If the alternative has uncertain consequences and, hence, the node $\{H\}$ representing the alternative is a chance node, then the utility function is defined as:

$$U_{\{H\}|c} = v^0_{\{H\}} + v^1_{\{H\}|c} + \varepsilon_{\{H\}|c} \tag{12}$$

and if the alternative is followed by a next decision and, hence, the node $\{H\}$ representing the alternative is a decision node, the utility function is defined as:

$$U_{\{H\}|c} = v^0_{\{H\}} + E\left(\max_i \left(U_{\{H,i\}|c}\right)\right) + \varepsilon_{\{H\}|c} \tag{13}$$

where $U_{\{H,i\}|c}$ denotes the utility of class c given its i-th outcome of H, and, as before, $v^0_{\{H\}}$ denotes the base utility of the choice alternative represented by the node itself, $v^1_{\{H\}|c}$ denotes the class-dependent outcome-related utility and $\varepsilon_{\{H\}|c}$ is an unobserved error term.

The error term $\varepsilon_{\{H\}|c}$ is class dependent, which implies that (i) unobserved errors consists of two parts, a class dependent constant and a random effect which is unknown; (ii) random effects across trials and decisions made by one individual are independent of each other. This is justified because the error term in the early decision stage has already been conceptually "realized", thus its associated error term does not affect later choice alternatives anymore. Under this assumption, the expected maximum utility of next level alternatives can be replaced by a logsum function:

$$U_{\{H\}|c} = v^0_{\{H\}} + \ln \sum \exp(U_{\{H,i\}|c}) + \varepsilon_{\{H\}|c} \tag{14}$$

Furthermore, we assume the error term $\varepsilon_{\{H\}|c}$ of choice alternatives to be i.i.d.-extreme value distributed. This gives a logit form for the choice probability for each decision alternative.

Now, assume we have *N* individuals, each of them belonging to one of the *C* classes. Each individual makes *T* trials of sequential choices, each sequence of choices consists of *S* decisions, each decision has *J* alternatives. We define the probability of individual *n* choosing alternative *j* at decision *s* in trial *t* when this individual belongs to class c as:

$$P_{nts|c}(j) = Prob(y_{nts} = j \mid class = c) \tag{15}$$

where y_{its} denotes the choice made. Further, we define the probability of individual n choosing choice alternative *j* in trial *t* making the *s*-th decision given the class of this individual in logit form following the earlier assumption of the i.i.d.-extreme value distributed form of the error terms:

$$P_{njts|c} = \frac{\exp(v_{njts|c})}{\sum_{k=1}^{J}\exp(v_{nkts|c})} \tag{16}$$

The contribution of this individual to the likelihood of the model is the joint probability of decision sequence $y_n = \{y_{n1}, y_{n2}, ..., y_{nT}\}$, defined as:

$$P_{n|c} = \prod_{t=1}^{T}\prod_{s=1}^{S} P_{nts|c} \tag{17}$$

Or

$$P_{n|c} = \prod_{t=1}^{T}\prod_{s=1}^{S}\prod_{j=1}^{J} P_{njt|c}^{\delta_j}\ , \tag{18}$$

where δ_j =1 if the *j*-th alternative is chosen and 0 otherwise.

Let α_{nc} denote the probability that individual *n* belongs to class c. Then the membership function is defined as:

$$\alpha_{nc} = \frac{\exp(z_n\theta_c)}{\sum_{c=1}^{C}\exp(z_n\theta_c)}\ ,\ c=1\ldots C,\ \theta_c = 0 \tag{19}$$

where z_i denotes a set of observable attributes that may be psychological constructs or socio-demographic characteristics. z_i in this format is known as “concomitant variable” or “covariate variable”. θ_c denotes the unknown class parameters. Usually, θ_0 or θ_c is set to zero for the model identifiability. In this model, we set θ_c to zero. Equation (19) represents a general approach in latent class modelling which has different names, covariate variable latent class model, concomitant variable latent class model or latent class regression model. Thus, the latent class regression model generalizes latent class model by including covariates, concomitant variables to predict the latent class memberships for individuals. In this study, respondents’ age, gender and education level are chosen to be covariate variables.

The likelihood function for individual *n* across all classes is the weighted sum of the class specific contributions:

$$P_n = \sum_{c=1}^{C} \alpha_{nc} P_{nlc} \tag{20}$$

The log likelihood function for all observations is:

$$LL = \sum_{n=1}^{N} \ln P_n = \sum \ln\left(\sum_{c=1}^{C} \alpha_{nc} (\prod_{t=1}^{T} \prod_{s=1}^{S} P_{ntslc})\right) \tag{21}$$

where P_{ntslc} in likelihood function is $\prod_{j=1}^{J} P_{ijtslc}^{\delta_j}$, where $j \in J$ indicates a choice alternative.

DATA

The covariate variable latent class model of activity rescheduling and information acquisition behaviour was estimated using data collected in an interactive computer experiment that uses a travel simulator to collect travellers' activity rescheduling responses and their travel information acquisition behaviour in a set of hypothetical travel situations. The experiment is web-based and consists of two experiments each consisting of two uncertain events, labelled as delay 1 and delay 2, under similar activity context and geographical settings. In experiment one, two uncertain events happen sequentially in time, whilst in the second experiment two uncertain events occur concurrently. Respondents are invited to make choices on the basis of a narrative or storyline, implement these choices and receive feedback. The web-based simulator can be viewed as a state-dependent machine that presents situations to respondents according to current system states. It keeps a track of the respondent's decision history, current time, current location information and conditional on these, the simulator generates choice alternatives available dynamically for the current situation and gives feedback after implementing choices.

Settings

The respondents were presented with a hypothetical city in a web browser. They were asked to imagine the situation that they were living in a city and work at the fringe of the city. The layout of the city is shown on the screen. Possible activities to be conducted are: a farewell party for one of his colleagues (either from his own department or from other department) from 4:30 to 5 pm, a planned dinner/banquet with his friends at 6:45 to 7 pm, a shopping activity for some gifts for the dinner and a possible activity at home which is for changing dress and refreshment before heading to the dinner/banquet place together with his spouse. Possible delay locations are: 1) on the highway routes (delay 1) from work to the roundabout, 2) in the shopping area in inner city in experiment I or on the provincial road route in experiment II.

Hence, if no delays happen then the schedule in experiment I is as follows:

4.30 – 5.00 pm: farewell party of colleague (30 minutes)
5.00 – 5.30 pm: travel work to roundabout (30 minutes)
5.30 – 6.10 pm: buy flowers inner city (20 minutes)
6.10 – 6.40 pm: change dress and relax a bit (20 + 10 minutes)
6.40 – 7.00 pm: travel to dinner place (20 minutes)
7.00 pm: start dinner

In short, decisions a respondent has to make:

1. Leave earlier at 4:30 pm and skip the farewell party or leave normal at 5 pm

2. Go to flower shop in the inner city or skip buying flowers

3. Have a rest at home or skip it

Beside these decisions, a respondent can choose to buy travel information that predicts whether a delay will happen or not at particular locations (highway and inner city), only before departure from the work place.

Experiment II shares most of the features with Experiment 1 except:

1. There are two routes from work to the roundabout (highway and provincial road), and uncertain events (delay1 and delay2) are associated with these routes respectively

2. There is no uncertain event at the inner city for shopping

3. It is possible that either the farewell party or dinner or both are absent from the activity context.

These differences imply that an additional route choice decision after leaving work (early or normal) has to be made compared to Experiment 1. Furthermore, there are situations without time pressure on the activity schedule. For example, if no dinner is planned, there will be no shopping activity, and delay time on the route back home may play a minor role in route choice. Figure 1 shows the hypothetical activity travel environments for both experiments.

Experiment I is intended to look at schedule adaptation decisions in face of sequential uncertain events, whilst Experiment 2 is more concerned with baseline preferences, simultaneous delays that are more related to immediate action, since respondents will face two uncertain events simultaneously and have to make a choice between two uncertain alternatives. Delays are presented with probabilities and magnitudes in minutes. Respondents are informed that the probabilities are independent of each other and always represent their knowledge based on their experience with the space-time setting. So, respondents are asked to imagine that each case is completely independent of a previous case also with respect to their beliefs about delay probabilities. En-route information is not available, so it is not possible to acquire any information after leaving the work place. In both experiments, the transport mode is assumed to be the car.

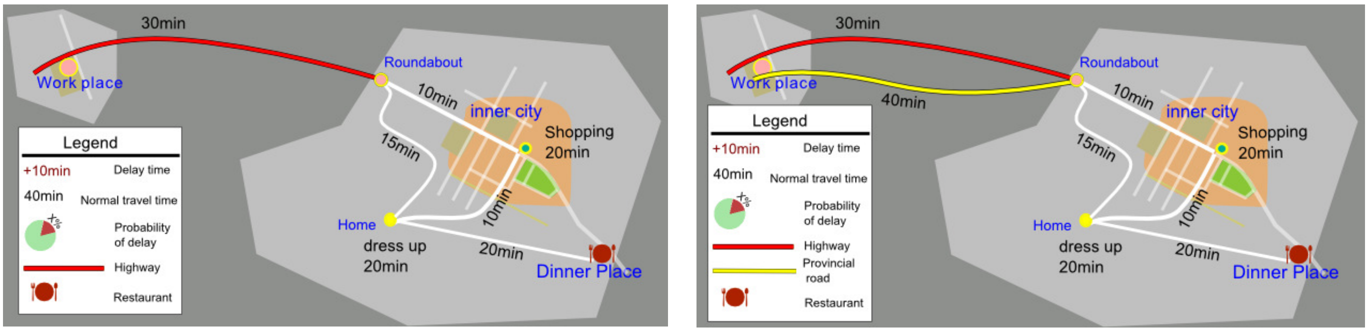

Figure 1 Hypothetical map used in experiment 1 and 2

Task

The task for the respondent is to organize his/her activities given different situations (different delay times, delay probabilities, for whom the farewell party is hold, with whom to have dinner together, etc) generated by the simulator by making choices at different decision moments. After each decision, the simulator executes a respondent's choice. The status (current time, current location, etc.) of the hypothetical travel environment will then be changed based on the choice made, and feedback (e.g. how much time is spent on which route, how long the delay is, etc.) will be given to a respondent. Figure 1 shows the way the situations were presented for the two experiments. In Experiment 1, delay 1 may happen on the way from work to roundabout on highway (red line) due to traffic jams. The other possible delay may happen at the city center in the flower shop due to queuing or finding a parking place. Travel time on each route is annotated in minutes. Shopping time and dress up time are also marked on the map.

In the second experiment, an additional route (provincial road, indicated by the yellow line) is available from work to the roundabout in addition to the highway. It also has an associated possible delay (delay 2). The shopping activity then is assumed to have a fixed duration with certainty, that is, no possible delay is involved at this location.

A completely random experimental design was used in this study. The control variables are shown in Table 1.

Table 1 Control variables in experiments

Experiment 1			
Control variable	levels	state	
Party	2	1	Planned party, only your couple are invited
		2	Planned party, other friends are also invited
dinner	2	1	Farewell party for colleague from other department
		2	Farewell party for a colleague from your group
Delay time 1	4	0	
		20 min	
		30 min	
		50 min	

Delay time 2	4	0	
		10 min	
		20 min	
		30 min	
Delay 1 probability	4	0.1	
		0.25	
		0.5	
		0.667	
Delay 2 probability	4	0.1	
		0.2	
		0.33	
		0.5	
Information reliability	2	80	80%
		100	100%
Information price	3	50	Euro cents
		100	Euro cents
		150	Euro cents

Experiment 2			
Control variables	levels	state	
Party	3	0	No party planned
		1	Planned party, only your couple are invited
		2	Planned party, other friends are also invited
dinner	3	0	No farewell party
		1	Farewell party for colleague from other department
		2	Farewell party for a colleague from your group
Delay 1 time	4	0	
		20 min	
		30 min	
		50 min	
Delay 2 time	4	0	
		10 min	
		20 min	
		30 min	
Delay 1 probability	4	0.1	
		0.25	
		0.5	
		0.667	
Delay 2 probability	4	0.1	
		0.2	
		0.33	
		0.5	
Information reliability	2	80	80%
		100	100%
Information price	3	50	Euro cents
		100	Euro cents
		150	Euro cents

MODEL ESTIMATION AND RESULTS

SAMPLE

Respondents were selected from a sample of neighbourhoods in the Eindhoven region. 417 respondents completed the interactive computer experiment (190 respondents were assigned to experiment 1 and 227 respondents were assigned to experiment 2 randomly by the travel simulator).

Model estimation

Parameters to be estimated include:
$\beta_{infoprice}$ denotes the parameter for information price.
$\beta^{j}_{leaveearly}$ denotes the parameter (the node constant v_0) for choice alternative leaving early from work, where $j \in \{1,2\}$, $j=1$ denotes the party is hold for a colleague from another department, while $j=2$ indicates it is for a close colleague from the same group.
$\beta^{j}_{nobuyflower}$ denotes the parameter (the node constant v_0) for not buying flowers for dinner, where $j \in \{1,2\}$ ($j=1$ if only respondent and his/her spouse are invited; $j=2$ if other friends have been invited).
$\beta_{highway}$ denotes the preference (the node constant v_0) for highway compared to provincial road.
$\beta_{traveldelay}$ and $\beta_{shoppingdelay}$ denote the base utilities of travel delay time and shopping delay time.
$\beta_{late\backslash k}$ denotes the disutility of being late for dinner when the dinner is planned for only the respondent and his/her spouse.
$\beta_{latedif\backslash k}$ denotes an additive term on disutility $\beta_{late\backslash k}$ in the situation that dinner is planned for the respondent and his/her spouse, with other friends also been invited. $k \in \{1,2\}$, $k=1$ denotes being late but less than 15 minutes, $k=2$ denotes being late more than 15 minutes.

Note that utility functions (see Equations 12 and 13) are class specific in their structure; the parameters are the same across all individuals. Also note that the parameter for buying flowers is specified as a disutility of not buying flowers for dinner, to be in line with the specification of utility for leaving work early (skipping the farewell party) which is also modelled as a disutility.

Parameters for covariate variables can be obtained simultaneously during the estimation. There are six parameters to be estimated in our setting: $\theta_1^{age}, \theta_1^{gender}, \theta_1^{edu\_level}, \theta_2^{age}, \theta_2^{gender}, \theta_2^{edu\_level}$, parameters for the third class are set to zeros as described in previous section.

The estimation was conducted utilizing a customized EM algorithm, which is an iterative optimization approach to estimate parameters given that part of the data is “missing” or “hiding”. It has enjoyed its popularity in estimating latent class models for years due to its stability, simplicity and easiness to implement.

RESULTS

Table 2. Estimation results

parameters	estimates	t-value		estimates	t-
$\beta_{infoprice}$	-0.0301	-66.4256	θ_1^{age}	0.0079	0.8011
$\beta_{leaveearly}^{1}$	-0.7949	-14.8406	θ_1^{gender}	-0.5482	-1.5675
$\beta_{leaveearly}^{2}$	-2.6844	-32.0850	$\theta_1^{edu\_level}$	-0.1742	-2.9170
$\beta_{highway}$	0.0537	0.9147	θ_2^{age}	0.0071	0.37451
$\beta_{nobuyflower}^{1}$	-2.0191	-29.3461	θ_2^{gender}	-0.5841	-0.7481
$\beta_{nobuyflower}^{2}$	-1.9892	-29.9018	$\theta_2^{edu\_level}$	-0.2375	-1.8257
$\beta_{traveldelay}$	-0.0643	-14.4922			
$\beta_{shoppingdelay}$	-0.0462	-8.3379			
β_{late1}	-0.3184	-3.5887			
$\beta_{latedif1}$	0.0149	0.1353			
β_{late2}	-1.4328	-11.2013			
$\beta_{latedif2}$	-0.0587	-0.3887			
Class 1: risk aversive		0.2143			
Class 2: risk taking		0.1467			
Class 3: risk neutral		0.6389			
Loglik NULL model		-17056.05			
Loglik		-9401.35			
AIC		18838.7			
BIC		18971.78			
McFadden's R-sq		0.4488			
McFadden's R-sq adjusted		0.4477			

*t-values are calculated via Hessian matrix, Fisher's observed information matrix, by numerical derivation of log likelihood function at maxima, which is approximated by EM algorithm. Other t-values are calculated using the same approach.

Since experiments 1 and 2 are special cases of the same decision tree structure, the data for the two experiments can be merged to estimate the structure. The results are shown in Table 2. All significant estimates give correct parameters signs. For example, the price parameter is negative, indicating the disutility of paying. The parameter for skipping the farewell party is also negative, suggesting a penalty for skipping the farewell party. Similarly, not buying flowers for the dinner has a negative sign also indicating a penalty in the utility function. Finally, the parameters for the delays (travel delay or shopping delay) also have negative signs. Thus, the signs of all estimated parameters are consistent with expectations, giving face validity to the results.

The magnitudes of estimates seem correct as well. The penalties for leaving early when the farewell party is held for a colleague of another department (-0.795) are not as bad as skipping the farewell party for a colleague from the own group (-2.684). Being very late (more than 15 minutes) for the dinner has a much higher penalty (-1.4328) than being late, later than planned time but less than 15 minutes, (-0.3184).

Class estimates indicates that 21.4% of the respondents in experiment adopted a worse case scenario heuristic to evaluate their choice alternatives, 14.7% respondents felt into the risk taking heuristic group and 63.9% respondents in risk neutral group.

Among three chosen covariate variables, covariates estimation suggest that age and gender do not have significant effect, whereas education level has a significant impact on the membership function. To interpret the covariate coefficients in general logit form, we calculate the predicted prior probability of class membership at varying levels of education level as an example and plotted their prior membership probability of being in each risk class as shown in Figure 2.

Both graphs show that respondents have strong tendencies to be risk averse when education levels are higher. In general, all travellers have lower probabilities of being risk neutral or risk taking.

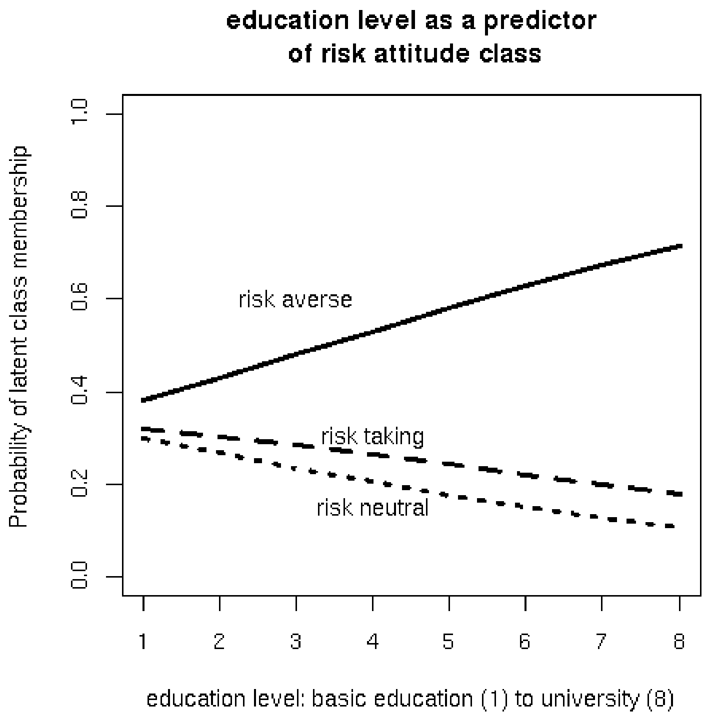

Figure 2 Predicted prior probabilities of latent class membership

CONCLUSIONS AND DISCUSSION

The goal of the present study is to better understand the relationship between travel information and comprehensive activity travel patterns under multiple uncertain events.

Based on previous studies, this study intends to explore the covariate effects in latent class model to better represent choice heterogeneity in activity based modelling field.

The results of this experiment provide evidence of face validity as the signs of the estimated parameters were consistent with a priori expectations. In addition, the relative magnitude of estimated parameters is interpretable.

The inclusion of socio-demographic covariate variables in the latent class heuristic model turns the previous latent class model into a full-fledged model for capturing heterogeneity in activity-travel decisions. Covariate variable education level has been proven to be a predictor for class membership. Higher educated people display higher probability of adopting a rational way of coping with uncertainty. On the other hand, covariate variables age and gender were not significant in the estimation. To verify their effects in this model, we need to either use a larger data set or reduce the number of variables. This remains to be an interesting aspect to be explored in future work.

The results of this study suggest that the utility of travel information is strongly dependent on time pressures and ability to make schedule adaptations to reduce negative consequences of delays. It means that when targeting different segments of the population, it would be most efficient, effective and cost-saving if the group of risk avoiders could be better targeted. The covariate latent class heuristic model, with the inclusion of socio-demographic covariate variables, can be used to better target market customers since decision styles are systematically related to socio-demographics characteristics. In doing so, marketing efforts could be improved. Acknowledgement is it.

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