

**Modelling and Appraisal of Smarter Choices:  
A Literature Review**

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## **1. INTRODUCTION**

WSP in association with Centre for Transport Studies (CTS) at Imperial College London, Mott MacDonald (MM), and the Denvil Coombe Practice (DCP) have been commissioned by the Department for Transport (DfT) to provide best practice guidance to users of transport models about how to model “Smarter Choices”. As part of the work programme, a review of the existing literature on the modelling of “Smarter Choices” and relevant transport and marketing literature on choice modelling was conducted in order to provide information on the current practice and to provide input for consideration of short-term and long-term recommendations.

The purpose of this document is to summarise the results from this review. The document is organised in a number of sections. The next section provides a brief overview of the salient features of the “Smarter Choices” type policies considered in the review and outlines some of the specific challenges associated with modelling the impact of these policies. Section 3 provides a review of a number of existing academic and applied studies that have attempted to explicitly model the effects of Smarter Choices. To complement this review of existing practice, section 4 provides a review of a number of modelling techniques from the transport modelling and marketing literature. Finally, section 5 presents some overall conclusions and recommendations. In presenting the material, we have deliberately avoided technical detail and have concentrated on principles and approaches.

## **2. OVERVIEW OF SMARTER CHOICES**

### **2.1 Smart Choice Measures**

Travel Demand Management (also called Transportation Demand Management in the US) refers to various strategies which aim to increase the overall efficiency of transport and reduce traffic congestion, energy use and pollution by affecting demand for travel rather than supply of infrastructure. These strategies may be categorised as “hard” measures which aim to shift the balance of travel time and travel costs in favour of sustainable transport modes (either through physical improvements to transport infrastructure or operation, traffic engineering, control of road space, or changes in price) or “soft” measures which aim to support and encourage change of attitude, perception, belief and behaviour towards sustainable transport modes. The latter are also known as Smarter Choices in the UK, Mobility Management in continental Europe and Travel Behaviour Change in Australia and NZ. Policy measures of this type are very diverse in nature but typical examples include:

- Workplace travel plans;
- School travel plans;
- Residential travel plans;
- Personalised travel planning;
- Public transport information and marketing;
- Travel awareness campaigns;
- Car clubs;
- Car sharing schemes;
- Teleworking;

- Teleconferencing; and
- Home shopping.

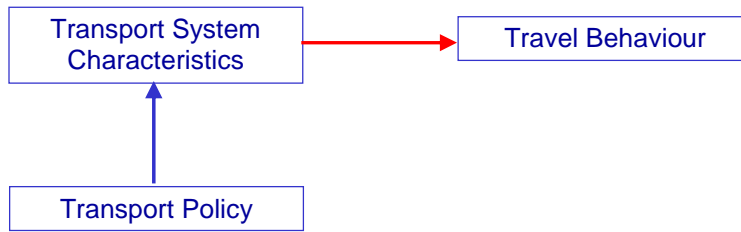
This document focuses on the modelling of these “soft” measures or “Smarter Choices”. The studies which do not have elements of “Smarter Choices” (for example, those modelling congesting charging or HOV lanes alone) are excluded from the review. Note that some “soft” measures may include elements of “hard” measures as well (for example, workplace travel plans often including parking management schemes). For more detail about “Smarter Choices”, see Department for Transport (2005) and Cairns *et al.* (2004).

## **2.2 Modelling Challenges**

Having set out the nature of smart choices measures, we believe it is useful to attempt to characterise the nature of the modelling challenges they pose, not least because there appears to be few if any attempts to do so in past. Figure 1 presents a summary of our thinking on this question. The essence of the challenge is that smart choices measures seek to exploit a much wider range of pathways through which to influence behaviour than to conventional policy measures.

Figure 1a depicts the situation that applies in the case of conventional policy measures. Here, the policy is defined in terms of changes to transport system attributes (usually travel time and travel cost but sometimes other attributes as well) and changes in travel behaviour are viewed as the result of changes in these transport system attributes. The modelling task is therefore to adequately characterise the relationship between changes in transport system attributes and changes in travel behaviour.

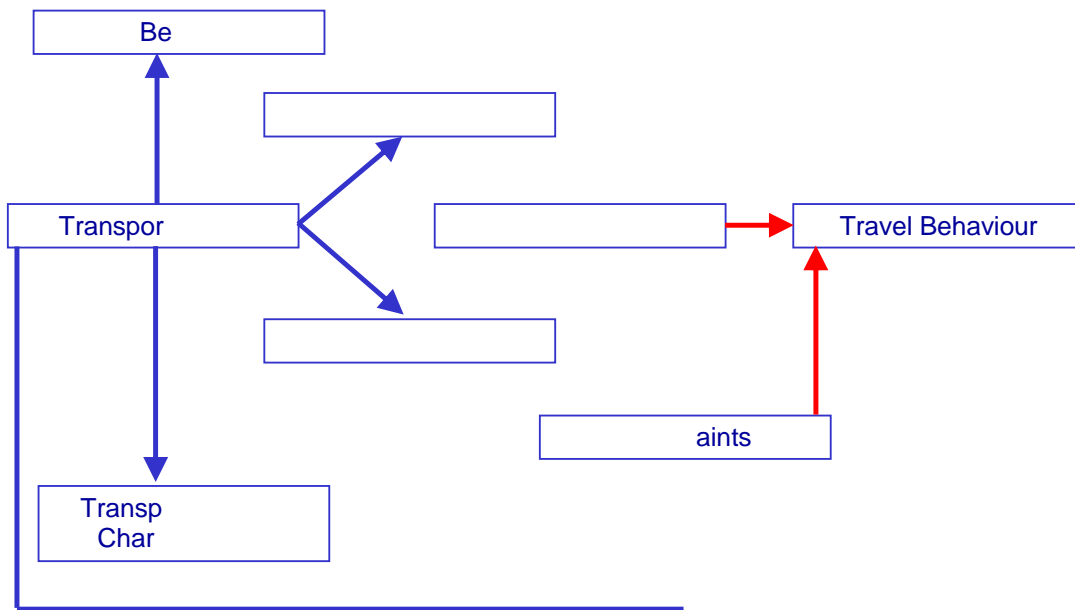
Figure 1b depicts the situation that applies in the case of smart choices measures. Underlying these measures is a more complex conceptual model of behaviour which posits the existence of background beliefs (e.g., belief in anthropomorphic climate change), attitudes towards specific travel alternatives (e.g., dislike of public transport), perceptions (e.g., regarding car travel costs) and constraints (physical or informational) all of which combine to give rise to behavioural intentions and ultimately to expressed behaviour. In this view, changes in behaviour are therefore seen as arising not only from the changes in transport system attributes, but also from changes in these beliefs, attitudes, perceptions and constraints and indeed smart choice measures are typically targeted at precisely these (non time and cost) features. The modelling task is therefore considerably more complex, since it involves characterising both how smart measures policy interventions affect beliefs, attitudes, perceptions and constraints and how these changes in turn ultimately affect behaviour.



$$\Delta\text{Policy} \Rightarrow \Delta\text{System} \Rightarrow \Delta\text{Behaviour}$$

**Fig**

**itional Policy Analysis**



$$\Delta\text{Policy} \Rightarrow \left. \begin{array}{l} \Delta\text{System} \\ \Delta\text{Beliefs} \\ \Delta\text{Attitudes} \\ \Delta\text{Perceptions} \\ \Delta\text{Constraints} \end{array} \right\} \Rightarrow \Delta\text{Behaviour}$$

**Figure 1b Pathways of Influence in “Smart Choices” Policy Analysis**

The specific modelling and analysis challenges include:

- Dealing with latent quantities: Beliefs, attitudes and perceptions are not directly measurable in the same way that travel times and travel costs are. Generally, the best we can do is to measure various indicators of these latent concepts. This adds to the uncertainty and complexity of modelling.
- Dynamics: There are likely to be strong dynamical affects in the relationship between smart choices policies and changes in beliefs, attitudes and

perceptions, indeed advocates of smart choices measures typically emphasize the importance of cumulative impacts and reinforcement over time. This is an area that is generally rather weak, in respect both of existing data sources and modelling capabilities.

- Model specification and estimation: Although the empirical evidence is patchy and its interpretation is contentious, the general picture that emerges from the existing empirical literature is that the impacts of smart choices measures are quite small. This means that there will be significant statistical challenges associated with the identifying relevant parameters and overall effects.

### **3. REVIEW OF THE LITERATURE ON THE MODELLING OF “SMARTER CHOICES”**

In this review, we classify the existing approaches into three groups based on the level of analysis; namely the sketch planning approach, the conventional trip-based approach and the activity-based approach.

#### **3.1 Sketch Planning Approaches**

##### ***3.1.1 US FHWA’s TDM Evaluation Model***

The US Federal Highway Administration’s Travel Demand Management Evaluation Model (FHWA TDM Evaluation Model), developed by COMSIS Corporation in 1993, is a DOS-based software programme that estimates the vehicle-trip reduction effects of a wide-range of travel demand management strategies. The programme distinguishes between TDM strategies which are employer-based and those which are implemented by a local government or transport agency at an area-wide level.

The FHWA TDM Evaluation model allows the user to test a variety of strategies including:

- Employer support programmes for carpool, vanpool, and transit;
- Employer incentive programmes including improved walking time from a parking location or transit stop, and subsidies;
- Work hour management including flexitime, staggered working hour, compressed working week, and teleworking; and
- Area-wide TDM strategies including transit improvement, HOV lanes, and parking management.

The FHWA TDM Evaluation Model operates from a starting trip base that describes person, vehicle and transit trip rates in a study area (either in the form of zone-to-zone trip tables or total trips generated at an individual site) and then estimates the changes in these trip rates that would occur as a result of mode and/or time of day switching due to different TDM measures.

The calculation in the FHWA TDM Evaluation Model is based on two procedures; look-up tables and a logit pivot-point procedure. Employer support programmes and Work hour management are analysed using look-up tables, while strategies that affect

time and cost of travel are analysed using a logit pivot-point model. The look-up tables were developed based on empirical evidence.

The FHWA TDM Evaluation Model is distributed by McTrans ([mctrans.ce.ufl.edu/](http://mctrans.ce.ufl.edu/)). The demo of the programme can be downloaded from [mctrans.ce.ufl.edu/Demos/](http://mctrans.ce.ufl.edu/Demos/).

### 3.1.2 US EPA's COMMUTER Model

The COMMUTER model, developed by the US Environmental Protection Agency (EPA) in 2000 and updated in 2005, is a spreadsheet-based model that estimates the travel and emissions impacts of transportation air quality programmes, focused on commuting.

It is designed for Metropolitan Planning Organizations (MPOs) and state Departments of Transportation (DOTs) who are assessing the emissions impacts of various Transportation Control Measure Strategies, and individual employers who are assessing the likely effectiveness of various commuter benefit packages and other measures to facilitate use of commute alternatives. It is most appropriately applied to a single worksite, employment centre, or subarea for sketch-level analysis purposes.

The COMMUTER model allows the user to select from and test a variety of strategies including:

- *Employer TDM Support Strategies*: Non-monetary inducements to encourage employees to use alternative modes rather than drive alone. These include rideshare matching services, vanpool formation assistance, on-site transit information and/or pass sales, transportation coordinators, guaranteed ride home.
- *Alternative Work Schedules*: Arrangements such as flexible or staggered work hours, compressed work weeks, and telecommuting.
- *Travel Time Improvements*: On-site or adjacent area modifications to improve access to work sites from transit, or by walking or biking. Also includes preferential (close-in/reserved) parking for carpools or vanpools, and improvements to transit service.
- *Travel Cost Changes*: Measures such as imposition of parking fees, differential rates or discounts for carpools or vanpools, transit fare subsidies, or in specific modal incentives or disincentives to any or all modes.

The calculation methodologies are largely based on those used in the Federal Highway Administration Travel Demand Management Evaluation Model (FHWA TDM Evaluation Model). As with the FHWA TDM Evaluation Model, the COMMUTER model uses two procedures for calculating travel response to workplace commuting strategies:

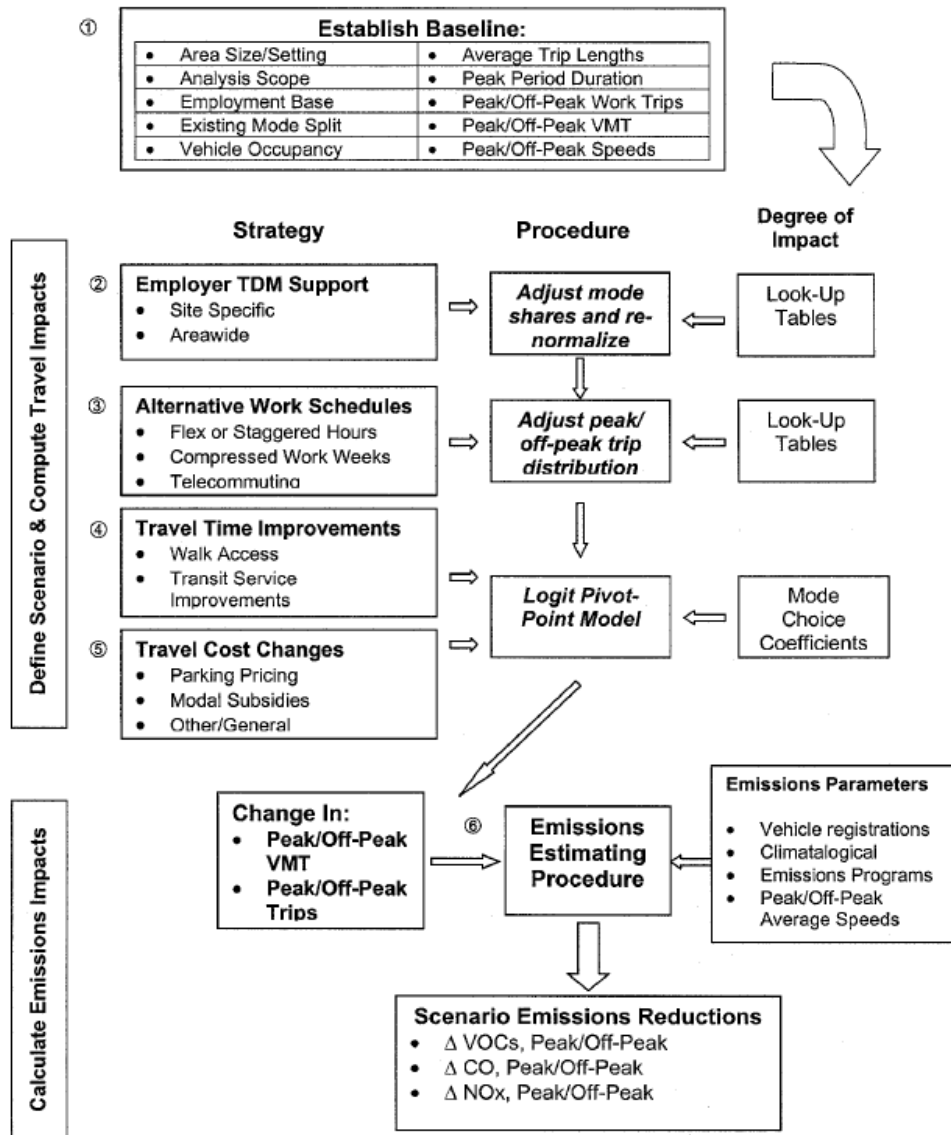
- *Look-Up Tables*: Relational factors from empirical research, arrayed in lookup tables where increments of change in trip rates are associated with particular types of programmes, reflecting different application assumptions, levels of intensity, and setting; and
- *Logit Pivot-Point Model*: A multimodal pivot-point model using coefficients and computational procedures from accepted logit-based mode choice models.



Employer TDM Support Programmes and Alternative Work Schedules are analysed using relational factors in look-up tables, while Travel Time Improvements and Travel Cost Changes are analysed through the more rigorous logit pivot-point procedure. Both procedures are subjected to a normalisation procedure applied to the adjusted shares to ensure that changes are proportionate across the available alternatives and do not allow final choices to exceed 100%. Figure 2 illustrates the COMMUTER estimating procedures.

The COMMUTER model differs from the FHWA TDM Evaluation model in that the COMMUTER model was designed to work with baseline mode share while the FHWA TDM Evaluation model was designed to work with baseline trip tables.

More detail about COMMUTER model can be found in Kuzmyak *et al.* (2005). The COMMUTER model itself can be downloaded from [www.epa.gov/oms/stateresources/policy/pag\\_transp.htm](http://www.epa.gov/oms/stateresources/policy/pag_transp.htm).



**Figure 2 COMMUTER Estimating Procedures**

Source: Kuzmyak *et al.* (2005)

### 3.1.3 CUTR's Worksite Trip Reduction Model (WTRM)

The Worksite Trip Reduction Manual and Web-based Model ([www.nctr.usf.edu/worksite](http://www.nctr.usf.edu/worksite)), developed by the Center for Urban Transportation Research (CUTR) at the University of Southern Florida in 2004, are tools that help predict the extent that each incentive, disincentive, or programme would impact traffic volumes and parking needs at a specific worksite.

This project used several thousand worksite trip reduction plans to build the model. The data came from three urban areas in the United States: Los Angeles, Tucson, and Washington State that have had trip reduction requirements on employers for many

years. The data consisted of worksite modal characteristics aggregated at the employer level and a list of incentives and amenities offered by employers.

The dependent variable chosen was the change in vehicle trip rate (VTR) (e.g., reduction of x vehicles per 100 employees). Two approaches were used for the model building process: linear regression models and non-linear neural networks. The linear statistical regression models were used as a benchmark for the validity and accuracy of the neural network models. Both techniques were applied to identify relationships between the change in VTR and features of the TDM measures implemented. Overall, the neural network models performed better than the linear regression models. The best generalized model for any location is the neural network model built on equally sampled data and this is the version deployed at [www.nctr.usf.edu/worksite](http://www.nctr.usf.edu/worksite).

TDM measures which can be evaluated in WTRM as summarized in Table 1.

**Table 1 TDM measures in WTRM**

TDM measures	Grouping
Facilities & amenities	<ul style="list-style-type: none"> <li>• Passenger Loading Areas</li> <li>• Other Facility Improvements</li> <li>• Preferential Parking Areas</li> <li>• Bike Racks and Bike Lockers</li> <li>• Shower and Lockers</li> </ul>
Guaranteed ride home programmes	<ul style="list-style-type: none"> <li>• TMA/TMO Provided Guaranteed Return Trip</li> <li>• Company Vehicle Guaranteed Return Trip</li> <li>• Emergencies Guaranteed Return Trip</li> <li>• Other Guaranteed Return Trip Programme</li> <li>• Rental Car Guaranteed Return Trip</li> <li>• Taxi Guaranteed Return Trip</li> <li>• Unscheduled Overtime Guaranteed Return</li> </ul>
Flexible timing	<ul style="list-style-type: none"> <li>• Flextime for Ride sharers (Work Shifts)</li> <li>• Flextime for Ride sharers (Grace Period)</li> </ul>
Marketing programmes	<ul style="list-style-type: none"> <li>• Commuter Information Center</li> <li>• Commuter Fairs</li> <li>• Focus Groups</li> <li>• Posted Materials</li> <li>• New Hire Orientation</li> <li>• Other Marketing Elements</li> <li>• Personal Communication</li> <li>• Company Recognition</li> <li>• Special Interest Club (Biking, Walking)</li> <li>• TMA/TMO Membership</li> <li>• Written Materials</li> <li>• Zip Code Meetings</li> </ul>
Ride share matching programmes	<ul style="list-style-type: none"> <li>• Regional Commuter Management Agency</li> <li>• Employer-Based Rideshare Matching System</li> </ul>
Financial incentives	<ul style="list-style-type: none"> <li>• Transportation Allowances</li> <li>• On-Going Bike-to-Work Subsidies</li> <li>• On-Going Carpooling Subsidies</li> </ul>

	<ul style="list-style-type: none"> <li>• Other Direct Financial Subsidies</li> <li>• On-Going Walk-to-Work Subsidies</li> </ul>
Parking management	<ul style="list-style-type: none"> <li>• Increased Parking Costs for Drive Alones</li> <li>• Other Parking Management Strategies</li> <li>• Subsidized Parking for Ride sharers</li> </ul>
Telecommute programme	<ul style="list-style-type: none"> <li>• Work at Home</li> <li>• Work at Satellite Center</li> </ul>
Compressed work week programme	<ul style="list-style-type: none"> <li>• 3/36, 4/40, 9/80 &amp; other Compressed Work Week Schedule</li> </ul>
Onsite incentives	<ul style="list-style-type: none"> <li>• Cafeteria, ATM's, Postal, Fitness Center</li> <li>• Transit Information or Pass Sales</li> </ul>
Non financial incentives	<ul style="list-style-type: none"> <li>• Auto Services (Fuel, Oil, Tune-Up)</li> <li>• Gift Certificates</li> <li>• Free Meals</li> <li>• Other Direct Non-Financial Incentives</li> <li>• Catalogue Points</li> <li>• Additional Time Off with Pay</li> <li>• Drawings, Free Meals, Certificates, etc</li> </ul>
Commuter tax benefit incentives	<ul style="list-style-type: none"> <li>• Introductory Transit Passes or Subsidies</li> <li>• Subsidized Vanpool Seats</li> <li>• On-Going Transit Subsidies</li> <li>• On-Going Vanpooling Subsidies</li> </ul>

The manual also provides a number of look-up tables which can be used to estimate the change in vehicle trip rate (VTR) for a given transit share and baseline VTR for the 50 most applied combinations of TDM measures. More detail about the Worksite Trip Reduction Manual and Model can be found in Winters *et al.* (2004).

### 3.1.4 WSDOT's TDM Effectiveness Estimation Methodology (TEEM)<sup>1</sup>

TDM Effectiveness Estimation Methodology (TEEM), developed by DKS Associate for Washington Department of Transportation (WSDOT) in 2003 and updated in 2005, is a tool analysing the effectiveness of TDM and land use strategies for the Central Puget Sound Region (Seattle), Washington State. It draws on local data sources including the Washington State's Commute Trip Reduction (CTR) programme.

TEEM is designed to pivot off of observed or baseline conditions. It predicts the changes in travel patterns that would most likely result from a combination of TDM and land use strategies. Therefore, data is required that describe the baseline conditions (population, employment, distribution of employees by employer size, number of person trips by mode and purpose, quantity of transit service, pedestrian and bicycle facilities) that currently exist or would exist in the future without the implementation of any strategy. Baseline data have been developed for the years 2000, 2020 and 2030.

<sup>1</sup> This section is based on the review of the WSDOT's TEEM by the EU-MAX project (2007) and Winters *et al.* (2007) and WSDOT's TEEM related papers by Loudon *et al.* (2003) and Loudon *et al.* (2007).

TEEM allows testing of twenty different strategies, which include:

- Mode Shift Support Strategies
  1. Vanpooling
  2. Alternative Mode Subsidy
  3. Universal Transit Pass
  4. VanShare
  5. Guaranteed Ride Home
- Parking Management Strategies
  6. Restricted Parking Supply
  7. Parking Pricing at Employment Sites
- Alternative Work Schedules Strategies
  8. Telecommuting
  9. Compressed Work Week
- Programmatic and Policy Support
  10. CTR-Type Programmes for Smaller Employers
  11. Multi-Employer Transportation Management Associations (TMAs)
- Marketing and Promotion
  12. Marketing and Promotion
- Bicycle and Pedestrian Facilities
  13. Improved Bicycle Access
  14. Improved Pedestrian Access
- Non-Commute Strategies
  15. Shopping Trips
  16. Special Event Travel
- Land Use Strategies
  17. Increased Density Near Transit Corridors
  18. Increased Mixed-Use Development
  19. Increased Infill & Densification
- Increased Transit Service
  20. Increased Transit Service

The methodologies for all 20 strategies are designed to operate on the same baseline travel patterns. In most cases the cumulative effect from combining most strategies can be established by sequentially predicting the effect of one, then adjusting the baseline data and applying the next one (multiplicatively additive). Effects of strategies that address different markets can be combined directly (directly additive). For conflicting or synergistic strategies, correction factors are required for the combination of effects.

### ***3.1.5 CUTR's Trip Reduction Impacts of Mobility Management Strategies (TRIMMS) Model***

Trip Reduction Impacts of Mobility Management Strategies (TRIMMS), developed by the Center for Urban Transportation Research (CUTR) at the University of Southern Florida in 2007, is a spreadsheet-based practitioner oriented sketch planning tool for calculating the costs and benefits of TDM for comparative assessment and public decision making.

Analogous to the COMMUTER model, TRIMMS uses two procedures for calculating travel responses to TDM strategies. For the strategies that directly affect travel costs and travel times, a constant elasticity of demand function is used to estimate final mode share changes. For the support programmes, such as programme promotion or any other voluntary behavioural change measure, a set of diversion rates are used to calculate the final mode share changes. These diversion rates were developed based on a fix effect regression model where each of the support programmes enters into an empirical equation estimating the change in ridership as an explanatory variable in a context of interaction with the hard programmes (i.e., those directly affecting travel costs and travel times).

The data from Washington State Department of Transportation Trip Reduction Programme during the period of 1995 and 2005 was used in the analysis. The data reports information on worksite characteristics, such as firm size and industry type, employee mode share, and information of TDM programmes. Factor analysis was employed to reduce the number of explanatory variables. At the end, a predictive model that allows for interaction between qualitative variables was chosen as the one with the higher predictive power. A table of diversion rates was developed based on this predictive model to be used within the sketch planning tool

In TRIMMS, the user can evaluate the following employer support initiatives:

- Programme Promotion;
- Flexible Work Hours;
- Telecommuting;
- Guaranteed Ride Home Programmes; and
- Presence of Amenities (restaurants, ATMs, childcare).

More detail about TRIMMS can be found in Concas and Winters (2007). The sketch planning tool itself can be downloaded from [www.nctr.usf.edu/abstracts/abs77704.htm](http://www.nctr.usf.edu/abstracts/abs77704.htm).

### ***3.1.6 Transfund New Zealand's Travel Behaviour Change Evaluation Procedures***

Transfund New Zealand (Transfund) and the Energy Efficiency and Conservation Authority (EECA) commissioned Maunsell Australia, Pinnacle Research, and Booz Allen Hamilton to review New Zealand and international Travel Behaviour Change (TBhC) procedures and experience, and develop evaluation procedures and guidelines for practitioners in New Zealand (Maunsell Australia, Pinnacle Research & Booz Allen Hamilton, 2004).

In order to estimate the likely impact that the project will have on travel behaviour including changes in mode share, a number of default diversion rate profiles (mode share changes) were developed for different types of work travel plans, school travel plans and household/community based projects. These default diversion rate profiles were developed based on the reported results achieved by TBhC projects in New Zealand, Australia, and the United Kingdom in recent years. The default diversion rate profiles give the changes in mode share from car-as-driver to other modes including car-as-passenger, public transport, cycling, and walking, expressed as absolute percentage point decreases or increases.

In the case of workplace travel plans, there are two sets of diversion rates: Standard – where no public transport improvements are proposed and Alternative – where there are proposed public transport improvements. Within these two sets of diversion rates, a scoring system is used to select the appropriate profile for a given workplace travel plan. A project’s score is determined based on the anticipated or proposed measures to be included in the workplace travel plan, which include:

- Car parking management strategies;
- Public transport service improvements;
- Public transport subsidies;
- Improvements to walking/cycling facilities; and
- Promotion of ride sharing.

In the case of school travel plans, there are only two default diversion rate profiles for schools, one for primary and another for intermediate and secondary schools.

For household/community based initiatives, a project can be classified into two default diversion rates (standard and low). The “Standard” diversion rate value is applicable for most projects, while the “Low” diversion rate is applicable in situations where the proposal will implement fewer measures than “usual” household based programmes, e.g. a community travel awareness campaign on its own would not achieve the standard diversion rate, or where public transport services and cycling/walking facilities in the area are poor and no significant changes to these are envisaged as part of the TBhC proposal.

### ***3.1.7 Victorian TravelSmart Evaluation Procedure***

The Victoria Department of Infrastructure (DOI) commissioned Maunsell Australia to develop an evaluation procedure that describes the evaluation methodology, benefit values and assumptions, as well as an Excel based model that enables future evaluations of the TravelSmart programme to be undertaken (Maunsell Australia, 2006). This evaluation approach was based upon the work Maunsell Australia, in association with Pinnacle Research and Booz Allen Hamilton, completed for Land Transport New Zealand.

Similar to the Transfund NZ’s TBhC Evaluation procedures, default diversion rates are used to evaluate the impacts of Victorian TravelSmart programmes. However, in contrast to the Transfund Evaluation procedure, the Victorian TravelSmart Evaluation procedure only used the data from its TravelSmart programme to establish the default diversion rates.

Default diversion rates are established for each of the four different TravelSmart programme streams; i.e. workplaces, communities, schools and universities programmes. Low and high scenarios were established for the workplaces and communities programmes to represent the range of outcomes that have been observed and the uncertainty associated with the measurements. Unlike the Transfund Evaluation procedures, the selection of the diversion rates for the communities and workplaces programmes is not based on the scoring system, but based upon the judgment of the project evaluator. For the schools programme, diversion rates are

established for primary and secondary schools, as well as private and public schools. For the universities programme only one set of diversion rates were established as detailed information was only available for the 2004 Monash University programme.

## 3.2 Conventional Trip-Based Approaches

### 3.2.1 *Winters et al. (2007)*<sup>2</sup>

Winters *et al.* (2007) develops a methodology to calculate the impact of TDM programmes on a transport network. The objective was to quantify the impact of TDM measures on transport performance measures such as delay, average speed, and spatial and temporal extent of congestion on a network, in addition to vehicle trip reduction (VTR), vehicle miles travelled reduction and emission reduction. The paper used CORSIM, a microscopic traffic simulation, to compare the current performance of the network with a scenario in which the reduced vehicle trips due to the TDM programmes are added back onto the network.

The steps used in the analysis in this study are summarised as follows:

- A traffic network with documented data of employer-based TDM programmes in its surrounding was selected.
- Worksites utilising TDM programmes within the impact area were inventoried.
- Time period for the analysis was defined.
- Data including worksite information, types of employer-based TDM strategies practiced, employee participation, and employee commute travel behaviour were collected.
- VTR at each worksite were calculated.
- VTR were then distributed (pairs of origin-destination trips) on the traffic network.
- The distributed trips were then assigned onto network links based on the shortest path between origins and destinations.
- The (already-calibrated) microsimulation model was run with existing volumes (Scenario A: with TDM).
- VTR (from step 7) were added to existing traffic counts on network links (Scenario B: without TDM).
- Scenarios A and B were run and data from output files were analysed to compare the scenarios.

The data for this study was obtained from the Washington State's Commute Trip Reduction (CTR) programme. CTR employers submit an annual report and a programme description form to report on TDM programmes implemented. CTR employers are also required to survey employee commute behaviour every two years to measure progress toward their CTR goals. Since the CTR employee biennial survey is conducted after the CTR programme is implemented, this study assumed that

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<sup>2</sup> In contrast to the modelling works in other studies in this review which was carried out at the appraisal stage of the programme, the modelling work in this study was carried out at the monitoring stage of the programme. However, it is included in this review as it provides a useful insight in how to apply a sketch level planning tool to a conventional transport model.



individual employee commute travel behaviour information in the survey is the scenario with TDM. However, since the implementation of TDM programmes vary across the employers, the definition of with TDM was not consistent. In other words, the scenario with TDM for one employer may differ from another.

While TDM is a broad application of different strategies aimed at reducing and/or eliminating SOVs, for the purposes of this research, these strategies are combined into four different groups and only the impact of these groups are evaluated (Table 2).

**Table 2 TDM Strategies analysed in Winters *et al.* (2007)**

Group	Strategies	Purposes	Scenarios A With TDM	Scenarios B Without TDM
A	Alternative work schedules	CWW and telecommuting	This group of strategies functions to reduce person trips.	Employees are not allowed to telecommute or participate in CWW.
B	Employer TDM support strategies	Nonmonetary promotions to encourage use of alternative modes. These include rideshare matching services, vanpool formation assistance, onsite transit information and/or pass sales, ETC, and guaranteed ride home.	This group of strategies functions to reduce the driving alone trips by encouraging employees to take alternative modes.	Employers do not assist in any way to encourage modes other than SOV
C	Travel cost changes	Measure such as imposition of parking fees, differential rates or discount for carpool or vanpool parking, transit fare subsidiaries.	This group of strategies functions to reduce SOVs by increasing SOV costs or decreasing that of alternative modes.	There is no financial subsidy for any alternative mode and SOV or other mode parking is free.
D	Flexible work hours	A relaxation in the official daily hours of business allows employees the flexibility to adjust their personal work schedules to either come early/leave early or come late/leave late to avoid the most congested portion of daily commute periods.	This group functions to shift vehicle trips out of peak period.	Employees are not allowed to work on flexible work hour schedules.

The process of estimating VTR was developed based on the COMMUTER model. The impact of each group of strategies is evaluated separately using different methods:

- The impact of alternative work hours is evaluated by adding participants of telecommuting and compressed work week (CWW) back to SOVs, then calculating the revised person trips.
- Employer TDM support programmes are analyzed using relational factors in look-up tables, along with a normalisation procedure applied to the adjusted

shares to ensure that changes are proportionate across the available alternatives and final choices do not exceed 100 percent.

- Travel cost changes strategies are analyzed through the more rigorous logit pivot-point procedure.
- The impact of flexible work hours is evaluated by estimating the number of vehicle trips shifted out of the peak period due to the programme.

### **3.3 Activity-Based Approaches**

#### **3.3.1 *Portland Activity Based Model System***

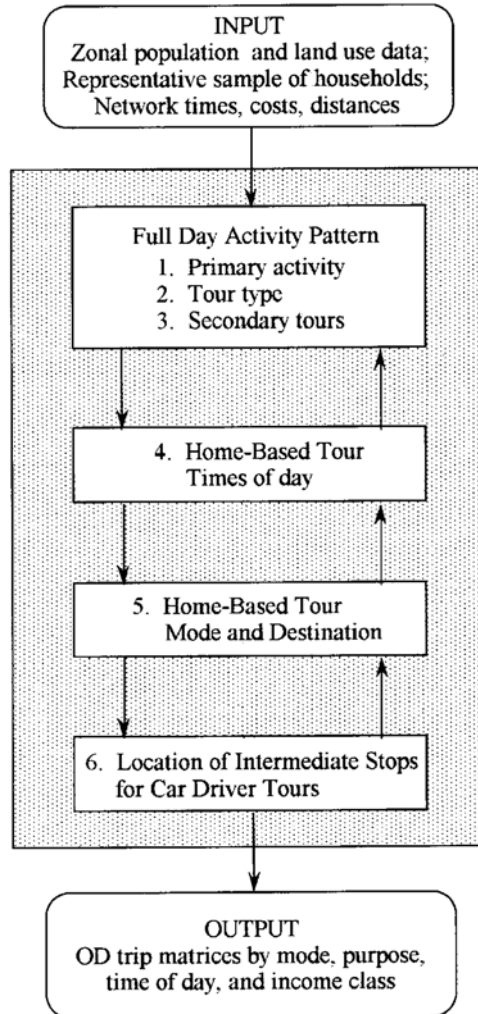
Shiftan and Suhrbier (2002) used the Portland activity-based model system which is based on the random utility modelling approach to forecast changes in travel behaviour as a result of TDM strategies. The model system is designed as a series of disaggregate logit and nested-logit discrete choice models, assuming a hierarchy of the model components. Lower level choices are conditional on decisions at the higher level, and higher level decisions are informed from the lower levels through logsum (accessibility) variables. Six main decisions are explicitly modelled in Portland's system. These can be summarised as follows:

- *Full day activity pattern and purpose of primary activity*: This model predicts a person's primary activity of the day as either work/school, household maintenance or discretionary, and as either at home, or as part of a tour away from home.
- *Trip chain type of primary tour*: The tour type is defined by the number and sequence of any intermediate stops made between home and the primary activity. For work tours, this model also determines whether or not there are any work-based "subtours" (trip chains beginning and ending at the workplace) that are made during the day.
- *Number, purpose, and type of secondary tours*: These tours are predicted simultaneously with the primary tour; thus, the model can capture the substitution between making multiple tours from home versus making additional stops during a single tour.
- *Timing of activities and travel*: A time of day model predicts the combination of departure time from home and departure time from the primary activity for each tour away from home.
- *Choice of mode and primary destination*: The key model applied at the tour level is a joint destination and mode choice model. The nine possible main modes are drive alone, drive with passenger, auto passenger, light rail transit (LRT) with auto access, LRT with walk access, bus with auto access, bus with walk access, walk, and bicycle.
- *Choice of locations for intermediate stops*: This choice is conditional on the main mode and on the location and timing of the primary tour activity.

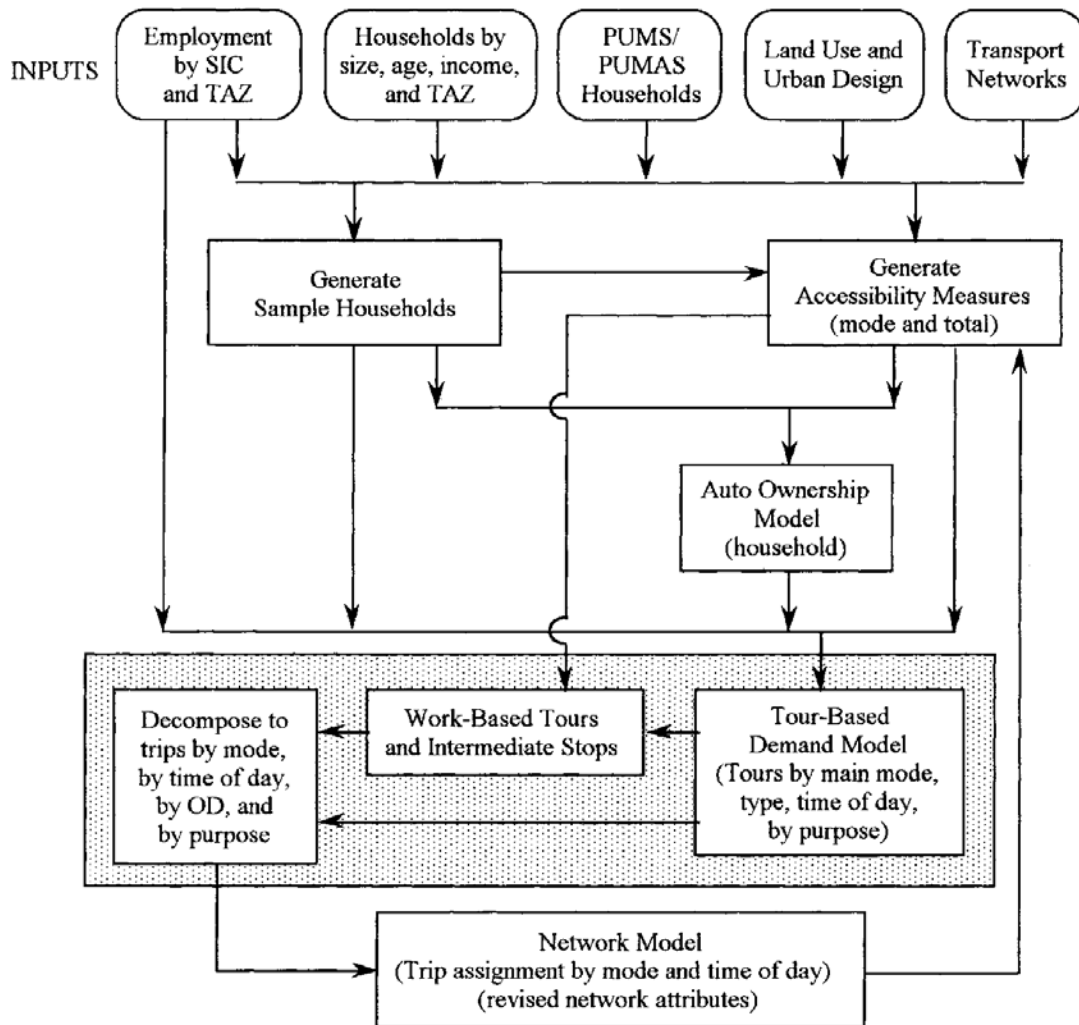
The models in the prototype system were estimated using data from the 1994 Household Activity and Travel Survey in Portland, Oregon. A total of 4,451 households were surveyed in the Portland region during 1994–1995. Respondents were asked to report on two consecutive days of activities with all seven days of the week included in the sample.

Figure 3 presents the Portland activity-based model system.

Figure 4 illustrates how this activity-based model system fits into the larger transportation forecasting process.



**Figure 3 Portland activity-based model system**  
Source: Shiftan and Suhrbier (2002)



**Figure 4 Overview of larger transport forecasting process**

Source: Shiftan and Suhrbier (2002)

TDM strategies evaluated in this study are summarised in Table 3.

In this study, the authors seemed to use only the Portland activity-based model system and a household sample enumeration technique to evaluate the effects of TDM strategies (i.e. no revised network attributes fed back into the model as illustrated in the larger transportation forecasting process). The traffic assignment was also performed for the base case and the combination of TDM policies to evaluate VMT and emission impacts for the two-and-a-half-hour a.m. peak period.

**Table 3 TDM strategies evaluated in Shiftan and Suhrbier (2002)**

Policy	Actions
1. Pricing of automobile travel	<ul style="list-style-type: none"> <li>○ Long-term parking cost is doubled in central city.</li> <li>○ SOV toll of one dollar is imposed for a.m.- and p.m. peak periods travel within the metropolitan area.</li> </ul>
2. Telecommuting incentives	<ul style="list-style-type: none"> <li>○ Double the current share of work-at-home activity (implemented by modifying the activity constant).</li> </ul>
3. Transit improvements	<ul style="list-style-type: none"> <li>○ Bus fare is halved for travel within the metropolitan area for all time periods.</li> <li>○ Increase bus service resulting in reduced bus waiting time by half for travel within the metropolitan area for all time periods.</li> </ul>
4. Combination	<ul style="list-style-type: none"> <li>○ Combination of policies 1, 2, and 3.</li> </ul>

### 3.3.2 Activity Mobility Simulator (AMOS)

AMOS (Activity Mobility Simulator) is an activity-based micro-simulator of daily human activity and travel patterns, which focuses on the adaptation and learning process that people exhibit when faced with a change in the transportation environment (Kitamura *et al.* 1995; Pendyala *et al.*, 1997,8). AMOS simulates a new activity engagement and travel behaviour pattern that a person is likely to adopt in response to a TDM strategy. This is accomplished through the implementation of several modules as illustrated in Figure 5. The detail of each module is summarised as follows:

- *Baseline Activity-Travel Analyzer*: This module reads individual trip records from a typical travel diary data set and compares them with network data for logical consistency and missing information. It then generates a coherent baseline activity-travel pattern for each individual to be used by the remaining AMOS modules.
- *TDM Response Option Generator*: This module creates the ‘basic’ or ‘primary’ response of an individual to a TDM strategy. The generator consists of a neural network model which was trained using the data from both revealed-preference and stated-preference surveys. The baseline activity-travel pattern from the previous module, demographic and socio-economic attributes and the characteristics of the TDM under investigation serve as inputs to this module. TDM measures may be characterized by changes in cost, travel time, modal attributes, and/or constraints that they bring about. The output of this module is defined by the basic behavioural response that a person is likely to exhibit in response to a TDM strategy. Various response options considered in AMOS include:
  - Do nothing different;
  - Change departure time to work/school;
  - Walk to work/school;
  - Bicycle to work/school;
  - Car/Van pool to work/school;
  - Take transit to work/school; and
  - Work at home.
- *Activity-Travel Pattern Modifier*: This module consists of a complex algorithm that can re-sequence and re-schedule activities, break and make trip chains,

and change travel modes and activity locations. The inputs of this module include the baseline activity-travel pattern, network data, land use data, socio-economic and demographic data, and the response option from the TDM Response Option Generator. The output of this module is a modified activity-travel pattern. The feasibility of the modified activity-travel pattern is checked for consistency and logic against a set of rule-based constraints that people must adhere to.

- *Evaluation Module and Acceptance Routine*: This component evaluates the utility associated with an activity-travel pattern based on the time allocated to various activities and travel in the pattern. Operationally, its built-in acceptance routine assesses whether a modified activity-travel pattern will be accepted or rejected on the basis of a human adaptation and learning model incorporating a set of search termination rules. The search termination rules are defined so as to permit the acceptance of sub-optimal choices of travel patterns. This is based on the notion of “satisficing” which postulates that an individual will experiment with a limited set of alternatives before choosing one that is satisfactory.
- *Statistics Accumulator*: This module reads all feasible and accepted activity-travel patterns provided by the Evaluation Module and Acceptance Routine to generate descriptive measures of travel on a daily basis.

AMOS was applied to the Washington, D.C. area for the Metropolitan Washington Council of Governments (MWCOC) (RDC Inc., 1995). A unique activity-based travel data set combining revealed preference and stated adjustment information was used in the model development and implementation phases of the effort. The survey included an activity-based time use section to obtain revealed preference information on daily activity and travel behaviour, and a stated adjustment (or stated adaptation) portion to obtain information on how individuals would respond in the event of TDM implementation. The TDM measures included in the survey are summarised in Table 4.

The respondents’ stated adjustments were coded into one of eight possible response options:

- Do nothing different;
- Change departure time to work/school;
- Walk to work/school;
- Bicycle to work/school;
- Car/Van pool to work/school;
- Take transit to work/school;
- Work at home; and
- Other (not specified).

**Table 4 TDM measures included in AMOS survey**

	Policy	Scenarios
TDM # 1	Parking pricing	Incremental parking tax at work place at - \$1 to \$3 per day in suburbs - \$3 to \$8 per day in D.C. and central areas
TDM # 2	Improved bicycle / pedestrian facilities	Well-marked and well-lighted bicycle paths and a secure place to park a bike wherever a person went
TDM # 3	A combination of TDM # 1 and TDM # 2	A combination of TDM # 1 and TDM # 2
TDM # 4	Parking pricing with employer-paid voucher	Employers provide employees with a commuter voucher while employees must pay for a parking surcharge. - \$40 to \$80 per month for both voucher and surcharge
TDM # 5	Congestion pricing with travel time reduction	Area-wide implementation of congestion pricing, effective from 6:00 AM to 9:00 AM and from 4:00 PM to 7:00 PM. - \$0.15 to \$0.60 per mile - 10% to 30% travel time savings
TDM # 6	A combination of TDM # 5 and TDM # 6	A combination of TDM # 5 and TDM # 6

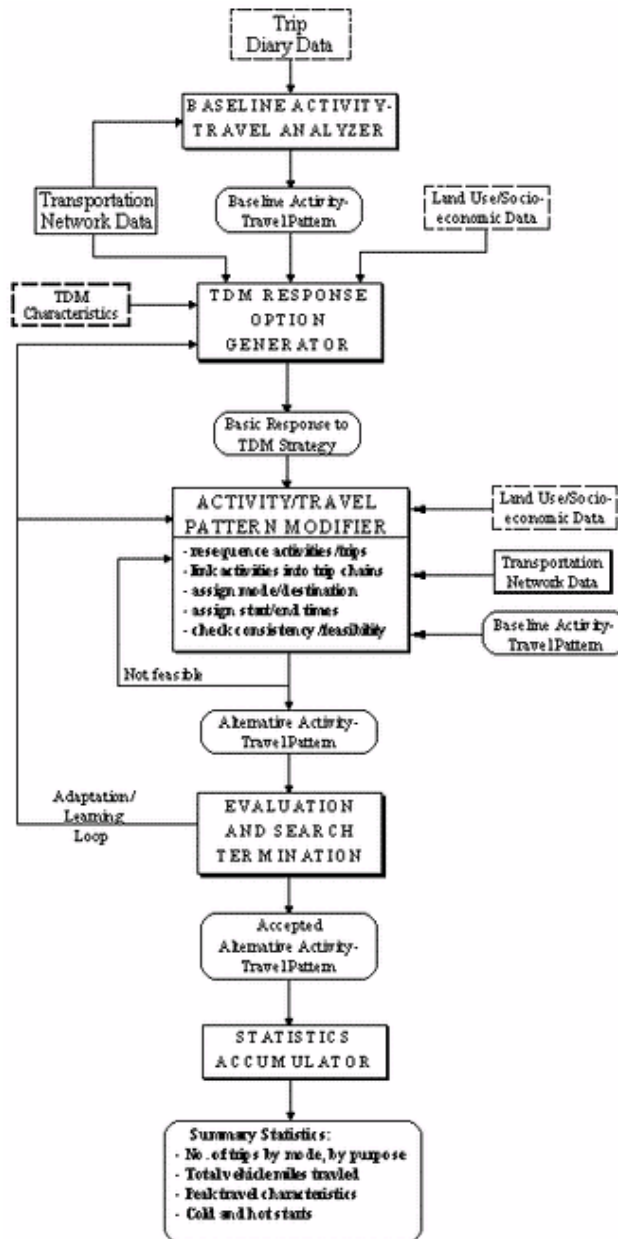
Upon the respondent providing a stated adjustment, a series of follow-up questions were presented to the individual to determine the impacts of the stated adjustment on their activity-travel pattern (i.e. secondary and tertiary changes in the activity-travel itinerary).

The data from a sample of 656 commuters from 656 households from AMOS survey were used to train the neural network. In the application part of the study, AMOS has been applied to a small subsample of 98 commuters from 1994 MWCOG Household Travel Survey to analyse the impacts of various TDM measures on a sample-wide basis. The TDM measures considered in the application part of the study are summarised in Table 5.

Note that improved bicycle / pedestrian facilities was not considered in the application part of the study because the responses to improved bicycle / pedestrian facilities were modelled separately using multinomial logit model (not included in the TDM Response Option Generator). This is because improved bicycle / pedestrian facilities is qualitatively quite different from the rest of the TDM strategies considered in the study.

**Table 5 TDM measures considered in AMOS**

	Policy	Actions
TDM # 1	Parking pricing	parking surcharge of \$8.00 per day
TDM # 4	Parking pricing with employer-paid voucher	parking charge of \$80 per month and a commuter voucher of \$60
TDM # 5	Congestion pricing with travel time reduction	congestion charge of \$0.50 per mile, travel time reduction by 30%
TDM # 6	A combination of TDM # 5 and TDM # 6	parking charge of \$80 per month, commuter voucher of \$60, and congestion charge of \$0.50 per mile



**Figure 5 AMOS Model Structure**  
Source: RDC, Inc. (1995)



#### **4. REVIEW OF RELEVANT TRANSPORT MODELLING AND MARKETING LITERATURE**

This section provides a review of relevant transport and marketing literature on the following topics:

- Models of relationship between choice and attitudes and perceptions – since “Smarter Choices” aim in part to influence behaviour indirectly via attitudes and perceptions
- Models of choice set generation – since “Smarter Choices” aim in part to affect the perceptions of options
- Models of traveller learning – since “Smarter Choices” aim in part to affect the perceptions of alternative by providing information
- Treatments of the effects of advertising and promotion in consumer choice modelling – since advertising and promotion measures form an important elements of many “Smarter Choices” programmes.

##### **4.1 Discrete choice models with attitudinal and perceptual data**

In the area of choice modelling, researchers have used various approaches to explicitly capture psychological factors such as attitudes and perceptions in choice models. These approaches can be grouped into two broad categories; (a) those that use the use of psychological factors as additional explanatory variables in the utility function and (b) those that use psychological factors for market segmentation. Most of the studies in this area are based on the first approach and various techniques have been used for these studies including direct inclusion of indicators in the utility, factor analysis followed by a choice model, integrated choice and latent variable model without explanatory variables for the latent variables and integrated choice and latent variables model with explanatory variables for the latent variables.

###### ***4.1.1 Direct inclusion of indicators in the utility***

One approach is to include indicators of psychological factors (such as responses to survey questions regarding individuals’ attitudes or perceptions) directly in the utility function. While this approach is very simple to use, it has been argued that these indicators are not causal, and they are highly dependent on the phrasing of the survey questions (Ben-Akiva *et al.*, 2002; Walker and Ben-Akiva, 2002). In addition, multicollinearity is likely to be a problem when a number of related indicators are included in the model (Ashok *et al.*, 2002; Walker and Ben-Akiva, 2002).

###### ***4.1.2 Factor analysis followed by a choice model***

Another frequently used approach is to first perform factor analysis on the indicators, and then use the fitted latent variables arising from the factor analysis as explanatory variables in the utility function.

For example, Choo and Mokhtarian (2004) studied the relationship of mobility, travel attitudes, personality, lifestyle, and demographic variables to individuals’ vehicle type choices, and developed a multinomial logit model for vehicle type choice based on these factors. The data for this study came from a 14-page mail-out/mail-back survey

of 1904 residents in the San Francisco Bay Area, conducted in 1998. The survey contains questions about objective mobility, subjective mobility, relative desired mobility, travel liking, travel attitudes, personality, lifestyle, excess travel, adoption and consideration of travel-related strategies, mobility constraints, and demographic characteristics; of which the details are given below:

- *Objective mobility*: respondents were asked about distance and frequency of travel by mode and trip purpose, as well as travel time for the commute trip.
- *Subjective mobility*: respondents were asked to rate the perceived amount of their travel on each of the same categories as in objective mobility on a five-point semantic differential scale ranging from “none” to “a lot”.
- *Relative desired mobility*: respondent were asked to rate the amount of travel they want to do compared to the present in each of the same categories as in objective mobility on a five point scale from “much less” to “much more”.
- *Travel liking*: respondents were asked to rate how much they enjoyed travelling on a five-point scales ranging from “strongly dislike” to “strongly like”.
- *Attitudes*: This part contained 32 attitudinal statements related to travel, land use, and the environment, to which respondents were asked to response on the five-point Likert-type scale from “strongly disagree” to “strongly agree”.
- *Personality*: Respondents were asked to indicate how well each of 17 words and phrases described their personality on a five-point scale from “hardly at all” to “almost completely”.
- *Lifestyle*: This part contained 18 Likert-type scale statements relating to work, family, money, status and the value of time.
- *Excess travel*: Thirteen statements asked how often on a three-point scale ranging from “never/seldom” to “sometimes” and “often” the respondents engaged in various activities that would be considered unnecessary or excess travel.
- *Adoption and consideration of travel-related strategies*: The data on past adoption and consideration of 17 travel-related choices ranging from buying a car stereo system to changing mode of travelling to work or moving house were collected.
- *Mobility constraints*: These constraints were measured by questions concerning limitations on travelling by certain modes or at certain times of day (with ordinal response categories from “no limitation” to “limits how often or how long” and “absolutely prevents”), the possession of a drivers’ license, and the availability of an automobile when desired.

The vehicle type choice considered in this study is defined as the vehicle type the respondent drives most often and is classified into nine categories; namely small, compact, mid-sized, large, luxury, sports, minivan/van, pickup, and sport utility vehicle. The key explanatory variables tested in the models can be grouped into 7 categories; namely objective mobility, subjective mobility, travel liking, attitudes, personality, lifestyle, and demographic variables. The 32 attitude indicators were reduced through factor analysis into six underlying dimensions: travel dislike, pro-environmental solutions, commute benefit, travel freedom, travel stress, and pro-high density. Using the same technique, the 17 personality indicators were reduced to four personality factors: adventure seeker, organizer, loner, and the calm personality, and

the 18 lifestyle indicators were reduced to four lifestyle factors: status seeker, workaholic, family/community-oriented, and a frustrated factor. These factor scores were then included as error-free explanatory variables in the utility function. The results indicated that travel attitudes, personality, lifestyle and mobility factors play an important role in vehicle type choice.

Cao and Mokhtarian (2005) examined the effects of objective and subjective variables on the consideration of 16 travel-related strategies<sup>3</sup> using the data from 1283 commuters from the same survey (Choo and Mokhtarian, 2004). They developed binary logit models for the consideration of each strategy. These strategies include:

- Buy a car stereo system;
- Get a mobile phone;
- Get a better car;
- Get a more fuel efficient car;
- Change work trip departure time;
- Hire somebody to do house or yard work;
- Adopt flexitime;
- Adopt compressed work week;
- Change from driving alone to work to other means;
- Buy equipment/service to help work from home;
- Telecommute;
- Change jobs closer to home;
- Move your home closer to work;
- Work part- instead of full-time;
- Start home-based business; and
- Retire or stop working.

The key explanatory variables tested in the models can be grouped into 10 categories; namely former adoption of a strategy, objective mobility, subjective mobility, relative desired mobility, travel liking, attitudes, personality, lifestyle, mobility constraints and demographic variables. As in Choo and Mokhtarian (2004), factor analysis was first performed on the attitudes, personality and lifestyle indicators and then the factor scores were included as error-free explanatory variables in the utility function. The results indicated that all these factors play an important role in the consideration of travel-related strategies.

While this approach addresses the causal issue of including indicators directly in the utility function, incorporating these factor scores as error-free explanatory variables ignores the fact that these variables contain measure error and therefore can lead to inconsistent parameter estimates (Ben-Akiva *et al.*, 2002; Ashok *et al.*, 2002). In order to obtain consistent estimates, the choice probability must be integrated over the distribution of the latent variables. This can be done through a two-stage approach where the factor scores and their distributions are first obtained from the factor analysis and then included in the utility function. While the estimates from this approach are consistent, they are still inefficient

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<sup>3</sup> One travel-related strategy “Changing from another mean of getting to work to drive alone” was not included in the analysis as the applicable subsample and its share of consideration were too small to support a viable model

### 4.1.3 *Integrated choice and latent variable models without explanatory variables*

A full information model in which confirmatory factor measurement models are integrated within the framework of choice models and estimated simultaneously could solve the problem of inefficient estimates (Ben-Akiva *et al.*, 2002).

Ashok *et al.* (2002) compared full information models with the choice model without latent variables, the choice model in which indicators are included directly in the utility function, and the choice model in which factor scores are included as error-free variables in the utility function using two different data sets.

The first data set came from a survey commissioned by a major cable television provider. The survey included a stated preference survey in which respondents were asked to state the likelihood of switching to a new service provider on a 0-10 scale given different values of pricing structure. The respondents were also asked to rate overall satisfaction and overall impression of the service on a 0-10 point scale ranging from "highly dissatisfied" to "highly satisfied", and response to a statement related to positive word of mouth of the service on a 0-10 point scale ranging from "completely disagree" to "completely agree". They were also asked to response to 5 statements related to possible barrier to switching on a 0-10 point scale ranging from "not at all likely to be a barrier" to "highly likely to be a barrier". Using exploratory and confirmatory factor analysis, the first three items were reduced to a latent satisfaction variable, whereas the next five items were reduced to a latent cost-of-switching variable.

Various model specifications for the likelihood of switching to a new service provider were tested including:

- An ordered probit model without latent variables;
- An ordered probit model in which indicators are included directly in the utility function;
- An ordered probit model in which factor scores for the two latent variables are included as error-free variables in the utility function;
- A full information model; and
- A full information model in which repeated responses are taken into account through individual and alternative specific error term.

The results indicated that model 5 is better than model 4 in terms of the goodness-of-fit and model 3 is better than models 2 and 1 respectively. Some parameters for the indicators in model 2 have unexpected signs which is due to multicollinearity. This is a common problem whenever perceptual and attitudinal indicators are directly included in the utility function.

The second data set from a customer satisfaction study conducted for a health care provider. The customer satisfaction survey was augmented with a stated preference survey in which a subset of current policyholders was exposed to a possible competitive offering and asked whether the policyholders would stay or leave. In the customer satisfaction survey, the respondents were asked to response to 8 statements

which were then reduced to two latent satisfaction constructs, namely the satisfaction with cost and the satisfaction with coverage, using the same technique.

Various model specifications for the choice of switching were tested including:

- A binary logit model without latent variables;
- A binary logit model in which indicators are included directly in the utility function;
- A binary logit model in which factor scores for the two latent variables are included as error-free variables in the utility function;
- A full information model; and
- Full information models with 2, 3, and 4 latent segments assuming invariant factor loading and invariant unique variance in the measurement models.

The results indicated that, with respect to the limited information models (models 1-3), the results are somewhat inconclusive, though favouring model 1. Similar to the first data set, none of the statistically significant satisfaction effects in model 2 has the proper algebraic sign. The full information model provides a different take on the importance of the latent satisfaction constructs than that suggested by limited information model forms (i.e. in the limited information models, these constructs are not significant), which would in turn provide managers with misleading results regarding the role of satisfaction. The full information models with latent segments provide statistically significant improvements in fit over the full information model where the goodness-of-fit measures point to the adequacy of 2 latent class solution.

While the full information approach proves to be superior to the limited information approach, all the abovementioned approaches are not capable for forecasting.

#### ***4.1.4 Integrated choice and latent variable models with explanatory variables***

More recently, integrated choice and latent variable models, in which the latent variables are related to the indicators and ultimately to the observable explanatory variables using structural equation models, have been used.

Ben-Akiva *et al.* (2002) presented a general methodology and framework for including latent variables in the choice models using this approach, together with three case studies.

The first case study (see also Morikawa *et al.*, 1996) presented the incorporation of the latent constructs of convenience and comfort in a mode choice model. The data for the study was collected in 1987 for the Netherlands Railways to assess factors that influence the choice between rail and car for intercity travel. The data contains revealed choices between rail and auto for an intercity trip and subjective evaluations of trip attributes for both the chosen and unchosen models. The 6 subjective evaluations of trip attributes were reported on a five-point scale ranging from “very poor” to “very good” and were used as indicators for latent variables. Two latent variables, ride comfort and convenience, were identified through exploratory factor analysis. They were also related to a number of explanatory variables including the characteristics of the traveller and the attributes of the modes through structural models. Estimation was done via sequential numerical integration: first the latent

variable model was estimated, and then the choice model (including integration over the latent variable) was estimated. This results in consistent but inefficient estimates. Binary probit models for mode choice both with and without latent variables were compared and it was found that the model with latent variables provided a better fit.

The second case study (see also Bernardino, 1996) assessed the potential for the adoption of telecommuting by employees. The data for the study was acquired through a stated preference survey. The behavioural hypothesis is that an employee faced with a telecommuting arrangement will assess the impact of the arrangement on lifestyle, work-related costs and income, and then decide whether to adopt telecommuting. The employee is assumed to have utility maximisation behaviour, and thus will choose to adopt a particular telecommuting option if the expected change in utility is positive. To obtain the indicators for the benefits, the employees were asked to rate the 11 impacts of the telecommuting programme on a nine-point scale ranging from “extremely negative” to “extremely positive”. To obtain the indicators for the costs, the employees were asked to response to 4 questions about the expected change in home office costs, child and elder care costs, and overall work-related costs on a three-point scale ranging from “decrease”, “remain the same” to “increase”. The latent variables for cost and benefit were related to the characteristics of the employee and the attributes of the telecommuting programme through structural models. A binary probit model for the adoption of telecommuting with latent variables for cost and benefit was estimated using a simultaneous numerical integration estimation procedure. The results indicated that this model contained more information and allowed for a clearer behavioural interpretation than standard choice models.

The third case study (see also Polydoropoulou, 1997) estimated the willingness to pay for an Advanced Traveller Information Systems called SmarTraveler. SmarTraveler is a service that provides real-time, location-specific, multi-modal information to travellers via telephone. This study used the revealed-preference and stated-preference data collected for the SmarTraveler test market in the Boston area. In the stated-preference survey, the respondents were presented with several pricing scenarios, and then asked what their usage rate (in terms of number of calls per week) or likelihood of subscribing to the service (on a four point scale ranging from “very unlikely” to “very likely”) would be under each scenario. Two types of scenarios were presented: a measured pricing structure in which travellers are charged on a per call basis (corresponding to SP1 responses) and a flat rate pricing structure in which travellers pay a monthly subscription fee (corresponding to SP2 responses). Travellers’ revealed preference for free service was reflected by the actual usage rate, which serves as an additional indicator of utility. Travellers’ satisfaction ratings (on a nine-point scale ranging from “extremely dissatisfied” to “extremely satisfied”) on 10 aspects of existing SmarTraveler service were used as indicators of the satisfaction latent construct. This construct was related to the characteristics of the traveller through a structural model. Ordered Probit models for the usage rate both with and without a latent variable for satisfaction were estimated using all three data sets (1 RP and 2 SPs). A simultaneous numerical integration estimation procedure was used and it was found that including a latent variable for satisfaction significantly improve the goodness of fit of the choice model.

Moikawa *et al.* (2002) also combined revealed preference data, stated preference data and perceptual data for a study of intercity travel mode choice. The data for this study

came from a home interview survey conducted in 1987 for the Netherlands Railways to assess factors which influence the choice between rail and car for intercity travel. The home interview survey consisted of one revealed preference survey and two stated preference surveys:

- The characteristics of an intercity trip from the City of Nijmegen to the Randstad made within the previous three months (RP data) and subjective rating of travel characteristics of both modes using a five-point rating scale ranging from “very poor” to “very good” for five perceptual indicators, and ten-point rating scale for an overall evaluation of the mode;
- Stated preference experiment of a choice between two different rail services; and
- Stated preference experiment of a choice between rail and car.

In both SP experiments, the respondents were asked which mode would be chosen for a particular intercity trip reported in the RP question in terms of a five point rating scales ranging from “definitely choose alternative 1”, “probably choose alternative 1”, “not sure”, “probably choose alternative 2” to “definitely choose alternative 2”.

Two latent variables, ride comfort and convenience, were identified through exploratory factor analysis and were related to a number of explanatory variables including the characteristics of the traveller and the attributes of the modes through structural models. A binary probit model was applied to the RP data, while ordered probit models were applied to the SP data. The estimation for the integrated model was done via simultaneous numerical integration. The results from the integrated model was compared to those from the models estimated using RP data alone, SP1 (rail vs. rail) data alone, SP2 (rail vs. car) data alone, RP data combined with SP1 data, RP data combined with SP2 data, RP data combined with both SP1 and SP2 data, and RP data with latent variables and it was found that the combination of RP and SP data helped identified coefficients of important variables and latent attributes identified by the structural equation model significantly improved the goodness-of-fit of the choice model.

Walker and Ben-Akiva (2002) proposed a generalised random utility model, in which random utility maximisation forms the core and extensions are added to relax simplifying assumptions and enrich the capabilities of the basic model. These extensions include:

- Flexible Disturbances in order to allow for a rich covariance structure and enable estimation of unobserved heterogeneity through, for example, random parameters;
- Latent Variables in order to provide a richer explanation of behaviour by explicitly representing the formation and effects of latent constructs such as attitudes and perceptions;
- Latent Classes in order to capture latent segmentation in terms of, for example, taste parameters, choice sets, and decision protocols; and
- Combining Revealed Preferences and Stated Preferences in order to draw on the advantages of the two types of data, thereby reducing bias and improving efficiency of the parameter estimates.

Using the same dataset as in Moikawa *et al.* (2002), various specifications of generalised model were tested including RP model, RP/SP model, RP/SP with random parameters, RP/SP with latent class to capture taste heterogeneity (two classes), RP/SP with latent variables of ‘comfort’ and ‘convenient’, and RP/SP with latent variables incorporating random parameters in both choice model and latent variable structural equations.

Due to complex multidimensional integrals, maximum simulated likelihood estimation was used in this study. The results indicated that the generalised models incorporating stated preferences and random taste variation greatly improved the fit of the model, whereas latent variables and latent classes had less significant impacts. The generalised model incorporated the better fit of the random parameter specification with the behavioural richness of the latent variable specification.

Recently, Johansson *et al.* (2006) have studied the effects of attitudes and personality traits on mode choice (train, bus and car) behaviour. The data for the study came from a survey of commuters between Stockholm and Uppsala conducted in 2001. Apart from socioeconomic questions and questions regarding the respondent’s habitual and alternative modes of travel and their respective times and costs, the survey also contained questions about respondent’s behaviour and attitudes. The respondents were asked to response to 9 behavioural questions related to transport-related safety behaviour and individual’s consumer and recycling habits on a five-point scale ranging from “never” to “always” and 11 attitudinal questions related to modal comfort, convenience and flexibility on a five-point scale ranging from “not important at all” to “very important”. These indicators were reduced to five latent variables namely environmental preferences, safety, comfort, convenience, and flexibility using factor analysis. These latent variables were then related to the characteristics of respondents through structural equation models.

Multinomial probit models (with varying choice set) both with and without latent variables were estimated. The estimation was performed in two steps where the latent variable model was estimated first and then the discrete choice model with integration was estimated. Thus the estimates were consistent but inefficient. The results indicated that the model with latent variables outperformed the model without ones.

#### **4.1.5 The use of attitudinal data for market segmentation**

Attitudinal data can also be used for market segmentation. Outwater *et al.* (2003) studied a mode choice behaviour in which attitudes were used for market segmentation. This study used the data from a household survey of residents of Bay Area, who were making trips in the TransBay or potential ferry market, and from a ferry on-board survey conducted in 2001. The household survey included a stated-preference exercise, in which respondents were presented with four choice experiments, each with four travel alternatives tailored for the specific trip that they took. The four alternatives included drive alone, carpool, rail or bus transit and ferry, and in the case of rail/bus transit or ferry, modes of access and egress to and from the rail/bus or ferry. The survey also included 30 attitude questions that the respondents had to rank on a scale from 0 to 10. For the on-board survey, riders were asked all the travel details of their current trip, socioeconomic status and attitude questions, similar to those asked in the household survey.



The 30 attitude indicators were reduced through factor analysis to 6 factors namely desire to help the environment, need for time savings, need for flexibility, sensitivity to travel stress, insensitivity to transport costs, and sensitivity to personal travel experience. Then a structural equation model (SEM), in which the six attitudinal factors were related to the 30 attitudinal statements and ultimately to available socioeconomic variables, was developed. Cluster analysis was used for segmentation based on the attitudinal factors derived from SEM. At the end, eight market segments were identified using three attitudinal factors. Multinomial logit models for mode choice for different trip purposes were developed based on this segmentation using the data from the stated preference exercise. Fourteen alternatives were specified, including two auto modes (drive alone and carpool), six bus/rail modes differentiated based on access/egress modes, and six ferry modes differentiated based on access/egress modes.

#### ***4.1.6 Inclusion of attitudinal data in large-scale travel demand forecasting***

In forecasting, Outwater *et al.* (2003) applied the survey-based market segmentation model mentioned above to the whole population in the San Francisco Bay Area. TAZ-level socioeconomic and demographic data for the target year were used to calculate the score of each attitudinal factor using the estimated parameters from Structural Equation Model. The resulting scores of the attitudinal factors were then used to divide the Bay Area population into eight segments to be used in mode choice and ridership forecasting models.

Another example of the inclusion of attitudinal data in large-scale travel demand forecasting is given by Steg *et al.* (2001). They presented a model for car-use simulation in the Netherlands (MOCASIN) which forecasts car use on an individual level on the basis of socio-economic, socio-demographic and motivational characteristics. The development of MOCASIN involved three steps. First, the relationships between car mileage and socio-economic, socio-demographic and motivational determinants were examined through regression analysis for nominal variables. Second, scenarios were constructed which differ in future developments in these determinants, based on existing Dutch long-term economic scenarios. Third, a Population Model was constructed for estimating the size and composition of the Dutch population for the years 1995, 2010 and 2020 according to these scenarios. Two versions of the Population Model were developed, i.e., a “basic” and an “extended” version. In the “basic” version, only the effects of changes in the composition of the population, classified according to age, level of educational attainment, gender, household composition, and household income were explicitly simulated. In this case, it is assumed that motivations within homogenous groups do not change over time. In the “extended” Population Model, developments in motivations were explicitly simulated too.

The regression analyses were conducted on a data set comprising a representative sample of the Dutch population, the “NIPO-Telepanel”. Respondents received a questionnaire every week on a variety of topics via a modem connection to a personal computer given on loan to each member of the panel. The answers were also returned via the modem. The data set used in this study was part of a questionnaire on environmental behaviour and attitudes. Car use was measured by asking respondents how many kilometres they travelled by car per week as a driver. Problem awareness

(a motivational factor) was measured by asking respondents to what extent they thought car use in the Netherlands contributes to environmental pollution on a seven-point scale ranging from “very little” to “very much”. In conclusion, the motivational factor of problem awareness was found to make a unique and important contribution to explaining the variance in car-use behaviour in addition to the other variables included in the analysis.

The second step involved the construction of scenarios on future developments in the determinants of car use. Three scenarios differing in the expected international economic and political developments and in national demographic, socio-cultural, technological and economic developments were developed. Given the scenario characteristics that are elaborated and given presumptions from Cultural Theory, assumptions and quantifications were made on developments in problem awareness. Sensitivity analyses were performed to check whether the model outcomes were sensitive to changes in assumptions on developments in problem awareness.

In the third step, a Population Model was constructed for 1995, 2010, and 2020 according to the three respective scenarios on developments in the determinants of car use described above. The calculation of the distribution of motivations in the Population Model can be explained as follows. For 1995, motivations were imputed. The seven classes of problem awareness from the NIPO-Telepanel were regressed on the five explaining variables of the Dutch Facilities Use Survey 1995 (i.e. age, gender, income, level of education, and household composition), resulting in probabilities for the classes of problem awareness. Random numbers were used to convert these probabilities into values realised for 1995. For 2010 and 2020, problem awareness was computed in accordance with the “1995” method in the “basic” model. This corresponds with the assumption of constant motivations within homogeneous groups. However, in the “extended” version, the classes of problem awareness were explicitly adjusted, in line with the assumptions of various scenarios.

## **4.2 Discrete choice models with choice set generation**

Another important effect of TDM measures is believed to be in changing the awareness and perception by travelers of alternative options, in particular alternative to the use of the private car. In choice modeling terms, this is an issue of choice set generation and over the past three decades, researchers have developed various techniques to address this issue. These techniques can be grouped into three broad categories namely (a) explicit choice set generation models, (b) implicit choice set generation models and (c) a variety of other approaches.

### **4.2.1 *Explicit choice set generation models***

One approach is to model the choice set generation process explicitly. This approach is normally based on the two-stage choice model suggested by Manski (1977) in which a consideration stage precedes choice. Different models have been proposed for the specification and calibration of this type of model.

For example, Swait and Ben-Akiva (1987) proposed a random constraint based approach to choice set generation. This approach considers an alternative to be available if a set of relevant constraints specific to that alternative are met. These

constraints may be elimination criteria which are used by individuals to arrive at a choice set and may not be the same across individuals.

Basar and Bhat (2004) proposed the use of a probabilistic choice set multinomial logit (PCMNL) model for an airport choice study. The model structure is based on Manski's two-stage choice paradigm in which the choice formation is modelled based on a random constraint-based approach and the choice given the choice set is modelled based on a multinomial logit formation. Based on the random constraint-based approach, an airport is excluded from the consideration set if the consideration utility for that airport is lower than some threshold consideration utility level. This threshold is assumed to be random and followed a standard logistic distribution. The consideration utility is also allowed to vary across individuals. As a result, the consideration for each airport can be modelled using a binary logit model. The probability of a choice set is obtained by first modelling the consideration probabilities for each alternative individually and multiplying the individual consideration probabilities appropriately. Such a procedure assumes that the consideration probabilities for any two alternatives are independent, except for the correlations due to common observed factors affecting consideration probabilities.

The primary data source for this study is an air passenger survey conducted by the Metropolitan Transportation Commission in the San Francisco Bay Area in 1995. This paper used the survey responses from business travellers from the three major bay area airports to the top thirty airports. As the data from some airport is oversampling, the Weighted Exogenous Sample Maximum Likelihood (WESML) method proposed by Manski and Lerman (1977) was used in the estimation. This method weights the log-likelihood value for each individual by the ratio of the market share of the airport chosen by the individual to the sample share of the airport chosen by the individual.

A PCMNL model was compared with a multinomial logit model and it was found that the PCMNL model outperformed the multinomial logit model in terms of data fit in both estimation and validation samples.

Cantillo and Ortuzar (2005) proposed a semi-compensatory two-stage discrete choice model incorporating randomly distributed thresholds for attribute acceptance. The semi-compensatory choice process of individuals is assumed to be characterised by attributes considering thresholds that set up a choice or rejection mechanism. If a threshold is surpassed by an attribute, the alternative is rejected. The process is followed eliminating alternatives sequentially. At the end of this first stage the remaining options (if more than one) constitute the choice set of the individual and then he/she will choose following a compensatory rule. The threshold could be random, differ among individuals and even be a function of socio-economic features and choice conditions.

The model specification used in the application part of the study is similar to the random constraint based approach, with the thresholds being independently left-truncated normally distributed and the choice conditional on the consideration sets modelled as a multinomial logit model. The data for the study came from a route choice state preference survey for car trips between the cities of Santiago and Valparasion in Chile. Participants were faced with two route choices at a time and

three variables were used in the experiment (i.e. travel time, toll charge, and number of fatal accidents per year).

Five models were tested including:

- A multinomial logit model;
- A proposed model with threshold for cost;
- A proposed model with threshold for time;
- A proposed model with threshold for accident; and
- A proposed model with threshold for accident whose mean is assumed to be a function of socio-economic characteristics.

The results indicated that model 5 is the best followed by model 4. Models 1, 2, 3 are equivalent and there is no evidence of threshold for cost and time.

Ben-Akiva and Boccara (1995) proposed discrete choice models with latent choice sets in which a choice set generation model is estimated using the information contained in responses to alternative availability questions. This is different from other studies in that it uses not only the observed choices but also indicators for alternative availability for the estimation. The model structure is also based on Manski's two-stage choice paradigm in which the choice formation is modelled based on a random constraint-based approach and the choice given the choice set is modelled based on a multinomial logit formation.

The data for the study came from a mode choice survey (driver alone, share ride, transit) conducted in the city of Baltimore, Maryland in 1977. The indicators used in this study are the recorded binary responses to the questions "Is (mode) available for your trip?"

First, a multinomial logit model was compared to a probabilistic choice set model (i.e. the model estimated without the information on alternative availability). For the multinomial logit model, it was assumed that drive alone is not available if the individual has no driver's license and share ride and transit are always available. For the probabilistic choice set model, it was assumed that share ride is always available whenever drive alone is available; this thus reduces the number of possible choice sets to 5. The random constraint specifications for the probabilistic choice set model was also specified as follows:

- Drive Alone is available to an individual  $n$  if his/her car availability is above an unobserved individual specific threshold; and
- Transit is available to an individual  $n$  if his/her walking distance to transit is below an unobserved individual-specific threshold.

By assuming that the thresholds are logistically distributed, the probability latent availability of each mode can be modelled using a binary logit model.

The results indicated that the probabilistic choice set specification fitted the data much better than the multinomial logit model.

Next, three integrated framework models, which differ in their specification of the measurement equations that related the alternative availability indicators and the latent variables of the problem were estimated.

The results indicated that while the values of parameter estimates varied substantially between the multinomial logit model and the probabilistic choice set model, the values of parameter estimates were very similar between the probabilistic choice set model and the integrated framework models.

Another study which used the information on alternative perception in the estimation is Cascetta et.al. (2002). They developed a model of route perception in urban road networks. The proposed model was developed in two steps. In the first step, an overall set of feasible routes encompassing all perceived routes was generated by a coverage factor maximising processes. In the second step, the probability that a given path belongs to the perceived choice set of the generic user was modelled using a binary logit model. The route perception model is based on the random constraint based approach. It is assumed that individuals do not consider alternatives that do not meet certain criteria (or thresholds) on single attributes or combinations of attributes and the value of this threshold for a given individual is unknown and distributed as a logistic variable.

The data for this study came from a survey of university students' and administration staff's home-based car trips in the city of Reggio Calabria, Italy. The questionnaires consisted of general information on the driver and specific questions on the pre trip route choice set selected, including a complete description of each perceived path. In this study, only the route perception model was estimated. While a two-stage approach is very popular, the main problem of this approach is the high degree of computational complexity associated with a large number of alternatives (more than six).

#### **4.2.2 *Implicit choice set generation models***

Another approach is to model the availability/perception of alternatives implicitly in the random utility choice model. This is typically done by introducing availability/perception attributes in the utility function of the alternative such as car availability or label variables. This approach is very convenient from the operational point of view as it allows the use of standard specification/calibration routines, and has been adopted more or less consciously in most specification of random utility models proposed in the literature (Cascetta and Papola, 2001). However, it lacks theoretical consistency as utility attributes are confused with availability attributes and misspecification errors may arise if the same attribute play a dual role.

Recently, Cascetta and Papola (2001) proposed an implicit availability/perception random utility model in which the intermediate perception degrees of alternatives are included in the utility function. In this approach, the degree of availability/perception of an alternative is represented by a continuous variable defined over the interval (0,1), with higher value representing higher degree of availability/perception of alternative and vice versa. The logarithmic transformation of this variable is included in the utility function such that the extreme cases are correctly represented; i.e. if the availability/perception of an alternative is close to 1, the factor log is close to zero and

does not influence the choice while if the availability/perception of an alternative is close to 0, the factor log is close to minus infinity and the alternative is definitely not available. In general, the degree of availability/perception of an alternative for an individual is not known to the analyst and it can be seen as a random variable with the mean modelled as a function of alternative and decision maker attributes. This model, named implicit availability/perception (IAP), can be differently specified depending on the assumptions regarding the joint distribution of random residuals and the way in which the mean availability/perception is modelled. In this paper, both first-order and second-order approximation of IAP logit models, in which the joint random distribution is iid Gumbel and the mean availability/perception is modelled as a binary logit model, are proposed.

These two models were tested against MNL model using the University of Napoli students' mode choice data (car, bus, metro, walk) and it was found that the second-order IAP logit model performed the best followed by the first-order IAP logit and the MNL respectively. C-Logit model proposed by Cascetta *et al.* (1996) can also be considered as a first-order approximation of IAP logit model where the average availability/perception of an alternative is directly simulated with the inverse of "commonality factor" of that alternative. This "commonality factor" captures the overlapping degree of that alternative and all other available paths connecting the same OD relation. C-Logit model was tested against MNL model using truck drivers' route choice data and it was found that C-Logit model performed better than the MNL model.

Note that IAP models can be estimated both with and without information on alternative availability/perception. For the former case, the estimation is analogous to that of a discrete choice model with latent variables (Ben-Akiva *et al.*, 2002) where this information can be seen as an indirect measurement of the alternative availability/perception latent variable.

#### **4.2.3 Alternative approaches to modelling choice set generation**

Horowitz and Louviere (1995) questioned the two-stage model of Manski and developed models of choice set generation based on the assumption that choice sets are not separate constructs per se, but are another expression of preferences, just as are choices. The paper hypothesised that an individual's preferences among the entire set of available alternatives can be described by a utility function that determines both the consideration set and the choice and that the utility of each alternative in the individual's consideration set is greater than the utility of every alternative not in this set.

The model based on the above hypothesis was tested against the models based on alternative hypotheses using the data sets on consumers' choices among supermarkets and brands of toothpaste. The results indicated that for the choice settings investigated, choices need not be modelled as a two-step process in which a consideration step precedes choice. However, the results also suggested that the role of consideration sets may depend on the choice context.

More recently, Swait (2001) introduced a new member of the generalized extreme value (GEV) family of discrete choice models called GenL (choice set generation

logit) model which directly incorporates choice set generation modelling into the specification via the GEV generating function. Though still a two-stage model of choice set generation and choice, the proposed model specifies choice set generation endogenously, and directly reflective of preferences, which differentiates it from the models in sections 4.2.1 and 4.2.2. The choice set probabilities need to make no use of exogenous information, but are instead taste-driven similar to Horowitz and Louviere (1995).

The data for this study came from a revealed preference survey of mode choice (air, train, bus, and automobile) of non-business intercity travellers between Sydney, Canberra and Melbourne in 1987. Five models were tested including:

- A multinomial logit model;
- A GenL model with full possible choice sets;
- A GenL model with full possible choice sets but with constrained scale parameters to guarantee the consistency with random utility;
- A GenL model with restricted choice sets to 1 and 2 modes; and
- A GenL captivity model in which the choice sets are restricted to 1 and 4 modes.

The results indicated that model 2 was the best model with regards to the goodness-of-fit followed by models 4, 5, 3, and 1 respectively. However, models 2 and 4 were not consistent with the random utility.

### **4.3 Models of traveller learning and behavioural adaptation**

Another aspect of many “Smarter Choices” measures is that they provide information to travellers. This is presumably on the basis of the assumption that travellers’ are inherently only partially informed regarding relevant features of the transport system and that provided information will stimulate learning and adaptation. The travel demand modelling literature has a long tradition of studying the subject of traveller learning and adaptation, especially as it relates to travel time. Therefore, in this section, we review the relevant literature in this area.

The existing models for travel time learning can be classified into three broad categories, namely (a) weighted average approaches, (b) adaptive expectation approaches and (c) Bayesian approaches.

#### **4.3.1 Weighted average approach**

In this approach, it is generally assumed that a traveller formulates the perception of the travel time in the current time period based on weighted average of travel times in previous time periods.

A number of models have been proposed based on the above assumption. However, they are different in terms of the assumptions regarding the travel times stored in the memory, the length of the memory, the function of weights, and the error component.

For example, Horowitz (1984) proposed three learning models in which travellers are assumed to have unlimited memory. The first two models assume that travellers can

acquire all the information about travel times from both the alternatives chosen and not chosen, while the third model assumes that travellers can acquire information only through their own experiences. Cascetta (1989) relaxed the assumption regarding unlimited memory by assuming the travellers can possess only a finite number of travel times from the previous time periods. However, he still assumed that travellers can acquire the information about travel times from the alternatives not chosen as well. The uniform weights were assumed in the empirical study. Polak and Hazelton (1998) proposed the model similar to Cascetta (1989), but the weights are parameterised according to a geometrically declining function.

Recently, Nakayama *et al.* (1999) proposed a model in which the perceived travel time is updated from the weighted average of  $n$  recalled experienced travel times and the maximum and minimum expected travel times on each alternative. The assumption regarding the weights in this study is quite different from the ones previously mentioned. In this study, the range of the perceived travel time elements is divided equally into  $L$  intervals, and a weight is assigned to each interval. This is equal to assuming that the weights depend upon the values of experienced travel times. Thus, the model is capable of representing different attitudes towards risk among different groups of travellers. Risk-averse travellers may have weights which are larger in higher ranges of experienced travel times, while risk-prone travellers may have weights which are lower in higher ranges. Another form of models which can be used to capture the attitudes towards risk in travel time perception was proposed by Nakayama *et al.* (2001). It is simply assumed that travellers update their perception of travel time based on the weighted average of the mean experienced travel times in the past and the difference between the maximum and minimum experienced travel times in the past. Risk-averse travellers may attach a larger weight to the difference between the maximum and minimum experienced travel times in the past, while risk-prone travellers may attach a smaller weight. Two types of model in which travellers possess limited and unlimited length of memory were proposed.

More recently, Ettema *et al.* (2003a) proposed a model in which the perceived travel time is updated based on the weighted average of the experienced travel times in the same class. It is assumed that travellers will first classify the experienced travel times from the previous time periods into mental classes. For each class, the experienced travel times will be ordered with respect to their ages and then assigned a rank order. The perceived travel time for each mental class is then updated based on the weighted average of the experienced travel times in that class where the weight is a decay function of the rank of the travel time in the class. Ettema *et al.* (2003b) extended the above model by assuming that the weight is not only a function of the rank of the travel time in the class but also a function of the deviation between that travel time and the perceived travel time for that class. This model is also capable of representing the attitude towards risk among group of different travellers.

While this type of model is applied widely, it is surprising to note that the empirical investigation of the model especially in the context of weight set is very limited. This is probably due to the complexity of the analysis. Another weakness of the model was pointed out by Iida *et al.* (1992). They argued that this type of model may not necessarily reflect the actual traffic phenomena when the choice is made repeatedly because other factors such as a magnitude of the discrepancy between the actual and



the perceived travel times and the regret in the past choices seem to be important in the actual choice behaviour.

#### **4.3.2 Adaptive expectation approach**

This type of model is probably the most frequently encountered in the literature. It is assumed that a traveller updates their perception of travel time on the basis of the magnitude of the discrepancy between the actual and the perceived travel times from the previous day.

A number of studies have been using this model for the travel time perception updating process; see for example, Cascetta and Cantarella (1991), Ben-Akiva *et al.* (1991), Vaughn *et al.* (1993), Emmerink *et al.* (1995), Axhausen *et al.* (1995), Van Berkum and Van der Mede (1998), Polak and Oladeinde (2000) and Jotisankasa and Polak (2006). Iida *et al.* (1992) extended the above model by including a constant or the learning bias into the model. The adaptive expectation model was also used to model queue length perception updating in van Berkum and van der Mede (1998).

The popularity of this type of model is based on its computational and conceptual simplicity; and on the plausible psychological interpretation of the model (Axhausen *et al.*, 1995; Polak and Oladeinde, 2000). Unlike other types of weighted average models, many empirical analyses of the parameters of the model were reported; see for example, Iida *et al.* (1992), Vaughn *et al.* (1993), Axhausen *et al.* (1995), van Berkum and van der Mede (1998), Oladeinde (2000), Polak and Oladeinde (2000), and Jotisankasa and Polak (2006). One of the disadvantages of this model is that the value of the perceived travel time is bounded by the values of the last experience and the prior perception; thus, the travellers cannot use their experiences on the previous days to help estimate the future travel conditions (Axhausen *et al.*, 1995).

#### **4.3.3 Bayesian approach**

An alternative approach to modelling travel time perception updating was proposed by Jha *et al.* (1998) and Chen and Mahmassani (2004). They developed a Bayesian updating model to describe how travellers update their perception of travel time on the basis of their previous perception and their experience. In the proposed framework, the mean travel time and the experienced travel time as perceived by each traveller are represented by random variables, whose variances are indicator of traveller's confidence of the source of information. Jha *et al.* (1998) proposed a model in which travellers are assumed to update their perception every day, while Chen and Mahmassani (2004) assumed that travellers may not update their perception every day and proposed three different mechanisms for triggering and terminating the updating process.

It can in fact be shown that the Bayesian and adaptive expectation approaches share a number of important structural similarities (Jotisankasa and Polak, 2005).

Note that even though this approach can treat variance (or the level of confidence) where the weighted average approach and adaptive expectation approach cannot, it also has a number of limitations. First, the variance of the mean perceived travel time always decreases from one day to the next. Second, the underlying travel time is

assumed to have a steady mean value. As a result, the model will not be applicable if there is any drastic change in the network. Moreover, some psychological experiments (e.g., Edwards, 1982) have shown that human prediction is consistently different from one based on the Bayesian updating model.

#### **4.4 Treatments of the effects of advertising and promotions in consumer choice modelling**

Advertising and promotion form a significant element of many “Smarter Choices” initiatives. Although some work has been undertaken, in general the travel demand modelling literature has not devoted significant attention to modelling the impact of advertising. However, within the marketing literature, modelling the impact of advertising on consumer choice behaviour has been a long standing theme and researchers have developed a number of approaches. These approaches can be broadly grouped into two categories, namely (a) modelling the effects of advertising and promotions on consumer choices through changes in consumer’s brand preferences and (b) modelling the effects of advertising and promotions on consumer choices through changes in consumer’s price sensitivities.

##### ***4.4.1 Modelling the effects of advertising and promotions through changes in consumer’s brand preferences***

One approach is to include variables indicating the level of advertising exposures and variables indicating the presences of promotional activities (such as in-store displays, feature ads, or price promotions) directly in the deterministic utility function. When these variables are included in the deterministic utility function, it is equivalent to assuming that advertising and promotional activities have direct effects on consumer’s brand preferences or brand utilities, broadly analogous to ASCs in the travel demand modelling context. However, when the interactions between these variables and other variables (e.g. brand loyalty) are included in the deterministic utility function, it is equivalent to assuming that other variables also have effects on the consumer responses to advertising and promotional activities as well. A dummy variable is normally used for the presence of in-store displays and feature ads; while the data on TV meter records of exposures to TV ads is normally used for the level of advertising exposures and, quite often, with non-linear transformation to account for the diminishing effects.

Various model specifications ranging from simple multinomial logit models to mixed logit models and dynamic multinomial probit models have been used to study the effects of advertising and promotions on consumer choice behaviour.

For example, Deighton *et al.* (1994) studied the effects of advertising exposures and promotions on household brand switching and repeat purchasing in mature and frequently purchased product categories (i.e., ketchup, liquid detergent, and powder detergent). A multinomial logit model for the choice of brand-size was developed based on consumer theories of framing and usage dominance. The theory of framing postulates that repeat purchasing effects of advertising can result from an interaction between advertising and brand usage whereby advertising serves to illuminate the brand usage experience. There are two types of framing, depending on the time sequence. If advertising precedes the experience, it is called “predictive framing” and

if advertising follows the usage experience, it is called "diagnostic framing". An additional mechanism is that the effects of advertising can be negated by the consumer's personal experience in using the product, which is called "usage dominance".

Explanatory variables used in the model include:

- Brand-size specific constant;
- Brand loyalty measured by the share of purchases of a brand made during the initialisation period;
- Size loyalty measured by the share of purchases of a size made during the initialisation period;
- A dummy variable for brand purchased on the previous occasion;
- Square root of the number of TV ad exposures between the current and previous purchase occasions and square root of the number of TV ad exposures between the previous and next previous purchase occasions;
- Interactions between the above two and a dummy variable for brand purchased on the previous occasion;
- Price at the current purchase occasion;
- A dummy variable if promotion is available at the current purchase occasion; and
- A dummy variable if a brand was bought on promotion at the previous purchase occasion.

A multinomial logit model have also been used by Pedrick and Zufryden (1991) to study the effects of advertising exposures and marketing mix variables (such as displays, feature ads and price promotions) in a frequently purchased low cost consumer product (i.e., yogurt). Explanatory variables used in the model include:

- Brand specific constant;
- Long-term brand loyalty measured by the number of purchases of a brand made during the initialisation period;
- Short-term brand loyalty measured by the number of purchases of a brand during the previous time period;
- Share of the number of TV ad exposures received prior to the current purchase occasion during the current time period;
- Price;
- Percentage price discounts promoted with a minor feature ad;
- Percentage price discounts promoted with a major feature ad;
- Value of store coupons; and
- Manufacturer coupon index measured by the number of brand manufacturer coupons redeemed during the week of current purchase.

Tellis (1998) studied the effects of advertising exposures and marketing mix variables on both brand choice and quantity choice in a mature product category (i.e. toilet tissue). He developed a tobit-like two stage model in which the first stage is a brand choice model (multinomial logit model) and the second stage is a quantity purchased given the brand choice model.

Explanatory variables used in the final brand choice model include:

- Brand-specific constant;
- Long-term brand loyalty measured by share of brand purchases made during the initialisation period;
- Logarithm of the number of TV ad exposures;
- Logarithm of the interaction between the number of TV ad exposures and long-term brand loyalty;
- Price; and
- Dummy variables for displays, feature ads, and manufacturer coupons.

Explanatory variables used in the final two-stage model include:

- Brand-specific constant;
- Long-term brand loyalty measured by share of brand purchases made during the initialisation period;
- Long-term volume loyalty measured by share of volume purchases made during the initialisation period;
- Number of TV ad exposures and its quadratic form;
- Interaction between advertising exposures and long-term brand loyalty and the interaction between advertising exposures squared and long-term brand loyalty;
- Price; and
- Dummy variables for displays, feature ads, and manufacturer coupons.

Jain *et al.* (1994) studied household brand choice behaviour for three frequently purchased product categories (i.e. saltine cracker, ketchup, and yogurt). A random coefficient logit model, which allows for unobserved heterogeneity in brand preferences and in the responses to marketing-mix variables, was developed for the study. The unknown underlying distribution of the unobserved heterogeneity is approximated by a discrete distribution. Explanatory variables used in the model include brand-specific constant, price and dummy variables for displays and feature ads.

Allenby and Lenk (1994) studied household brand choice behaviour for a frequently purchased product category (i.e., ketchup). A mixed logit model incorporating random coefficients to account for household heterogeneity and auto correlated error components to account for the dynamic effect was developed for the study.

Explanatory variables used in the model include:

- Brand-specific constant;
- Logarithm of household income;
- Logarithm of family size;
- Logarithm of price; and
- Dummy variables for displays and feature ads.

The random coefficients were assumed for the brand-specific constants, logarithm of price and dummy variables for displays and feature ads; thus, accounting for

unobserved household heterogeneity both in brand preferences and in the responses to marketing-mix variables.

Paap and Franses (2002) studied the long-run and short-run effects of marketing-mix variables on brand choice for a frequently purchased product category (i.e. saltine cracker). A dynamic multinomial probit model based on vector error-correction format in which current and lagged explanatory variables and lagged utility are included was developed for the study. The model also incorporates random coefficients to account for household heterogeneity. Explanatory variables used in the model include brand-specific constant, price and dummy variables for displays and feature ads.

#### ***4.4.2 Modelling the effects of advertising and promotions through changes in consumers' price sensitivities***

An alternative approach is to model the effects of advertising and promotions on consumer choices through changes in consumer's price sensitivities. This could be done in various ways.

For example, Allenby and Ginter (1995) examined the effects of in-store displays and feature ads on household consideration sets using a scanner-panel dataset of tuna purchases. In contrast to the two-stage models in which a consideration stage precedes choice (as shown in section 4.2.1), they adopted a single-stage model which allows for a less well-defined set of considered alternatives. A heteroscedastic logit model which allows for a flexible pattern of cross elasticities was developed for the study. This flexibility enables the model to describe price sensitivities among competing brands which correspond to competitive structure reflected in consideration sets. The model also allows for price sensitivities, and thus consideration sets, to be influenced by displays and feature ads of the brands.

Explanatory variables used in the deterministic utility function include brand-specific constant, logarithm of price (whose the coefficient was fixed to one), and dummy variables for displays and feature ads, and the standard deviation of the heteroscedastic error term for each brand was assumed to be a function of brand-specific constant, and dummy variables for displays and feature ads.

Papatla and Krishnanmurthi (1996) examined the dynamic effects of promotions on brand loyalty and customer's price sensitivity of the brand using a scanner panel data from the liquid detergent category. A multinomial probit model with time-varying coefficients accounting for the dynamic effects of promotions on brand loyalty, customer's price sensitivity, and subsequent responses to promotions was developed for the study. These time-varying coefficients were also assumed to be a function of the promotional purchase history of the household with some error terms to account for unobserved household heterogeneity.

Explanatory variables used in the deterministic utility function include:

- Brand-specific constant;
- Brand loyalty measured by a moving average of past purchases;
- Price;

- Dummy variables for displays and feature ads;
- Interaction between dummy variables for displays and price cut promotions;
- Interaction between dummy variables for feature ads and price cut promotions; and
- Interaction between dummy variables for displays, feature ads, and price cut promotions.

The coefficient of price was assumed to be a function of:

- A constant;
- Shares of coupon purchases, purchases on a feature with a price cut promotion, purchases on a display with a price cut promotion and purchases on a display and a feature promotion accompanied by a price cut promotion, among the purchases of the product during the initialisation period;
- Exponentially smoothed shares of coupon purchases, purchases on a feature with a price cut promotion, purchases on a display with a price cut promotion and purchases on a display and a feature promotion accompanied by a price cut promotion, among the purchases of the product up to the current purchase occasion; and
- Error terms to account for unobserved household heterogeneity.

Similarly, the coefficient of dummy variable for displays was assumed to be a function of

- A constant;
- Shares of purchases on a display promotion only, purchases on a feature with a price cut promotion, purchases on a display with a price cut promotion and purchases on a display and a feature promotion accompanied by a price cut promotion, among the purchases of the product during the initialisation period;
- Exponentially smoothed shares of purchases on a display promotion only, purchases on a feature with a price cut promotion, purchases on a display with a price cut promotion and purchases on a display and a feature promotion accompanied by a price cut promotion, among the purchases of the product up to the current purchase occasion; and
- Error terms to account for unobserved household heterogeneity.

The coefficient of dummy variable for feature ads was also assumed to be a function of

- A constant;
- Shares of purchases on a feature promotion only, purchases on a feature with a price cut promotion, purchases on a display with a price cut promotion and purchases on a display and a feature promotion accompanied by a price cut promotion, among the purchases of the product during the initialisation period;
- Exponentially smoothed shares of purchases on a feature promotion only, purchases on a feature with a price cut promotion, purchases on a display with a price cut promotion and purchases on a display and a feature promotion accompanied by a price cut promotion, among the purchases of the product up to the current purchase occasion; and

- Error terms to account for unobserved household heterogeneity.

Lastly, the coefficient of brand loyalty was assumed to be a function of

- A constant;
- Shares of purchases on a price cut promotion only, purchases on a display promotion only, purchases on a feature promotion only, purchases on a feature with a price cut promotion, purchases on a display with a price cut promotion and purchases on a display and a feature promotion accompanied by a price cut promotion, among the purchases of the product during the initialisation period;
- Exponentially smoothed shares of purchases on a price cut promotion only, purchases on a display promotion only, purchases on a feature promotion only, purchases on a feature with a price cut promotion, purchases on a display with a price cut promotion and purchases on a display and a feature promotion accompanied by a price cut promotion, among the purchases of the product up to the current purchase occasion; and
- Error terms to account for unobserved household heterogeneity

Note that the resulting model can be seen as a model in which the explanatory variables also comprise of the interactions between the variables normally found in the models from section 4.4.1 and variables representing the promotional purchase history of the household, and the complex error structures is characterised by these variables.

## 5. CONCLUSION

The existing approaches for modelling the effects of TDM can be classified into three groups, namely (a) sketch-planning approaches, (b) conventional trip-based approaches, and (c) activity-based approaches.

Sketch planning approaches are the most widely used and have been subject to significant development effort in the US and Australia. Although the details of different implementations vary, they are all based on the idea of distinguishing between ‘hard’ and ‘soft’ TDM measure and modelling the effects of each differently. Hard measures (i.e., those that operate principally via modifying travel times and costs) are handled using conventional demand modelling tools (such as pivot-point logit). Soft measures are modelled by modifying measured trip rates or mode shares according to the nature and intensity of the (soft) TDM measure(s) under consideration. The extent of this modification is quantified either by look-up tables or by regression models. Both approaches are data-intensive, requiring sample information both on the characteristics of TDM measures themselves and their impacts from a significant number of TDM measures.

As a short-term solution, the development of a similar approach would in principle be possible in the UK, but its feasibility depends upon access to sufficient, reliable data regarding TDM measures and their effects. Whether these data are available and/or available within reasonable timescale and effort is currently unclear. The key issue here is that there is a need to develop a proper scheme for the characterisation of “Smarter Choices” and an inventory of quantitative evidence of their impacts in

different circumstances. However, with different agencies using different approaches to monitoring and evaluation, this remains problematic. With regards to this, the data collected by the iTRACE system could provide a way forward. A brief summary of iTRACE is provided in Appendix A.

However, it is important to appreciate that this sketch planning approach should be seen, at best, as a short term solution. This is because it is essentially an ad hoc fix, devoid of any persuasive behavioural or theoretical justification, and as such exposes the analysis to unknown and unquantifiable uncertainties and biases.

In the longer term, we believe that is an urgent need to develop a more behaviourally and theoretically adequate treatment of TDM measures. Several of the existing activity based model in the literature (e.g., Kitamura *et al.*, 1995 Pendyala *et al.*, 1997,8 and Shifan and Suhrbier, 2002) demonstrate how a more adequate treatment of TDM measures can be imbedded within more synoptic modelling systems. And the work of Winters *et al.* (2007) shows how TDM effect can be ‘projected’ onto network performance outcomes.

A critical element of any effective advance in the treatment of TDM measures is the ability to represent the impact of ‘soft’ measures on travel behaviour. Here, our review of more advanced discrete choice modelling techniques demonstrates that credible and well-understood methods existing for accommodating:

- The impact of TDM measures on attitudes and perceptions;
- The impact of TDM measures on choice set generation;
- The impact of TDM measures on traveller learning; and
- The impact of TDM related advertising and promotion measures in consumer choice behaviour.

Although these methods are not widely used in practice, they are widely studied and well-understood in the academic domain and together form the basis for the development of a theoretically robust and defensible treatment of TDM measures.



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## **APPENDIX A: iTRACE OVERVIEW**

### **A.1 Introduction**

iTRACE is a Travel Plan management system developed by iBASE Systems Ltd with the support of WESTTRANS<sup>4</sup> and funding from Transport for London. It provides a centralised software suite designed to record, monitor, and report on the performance of Workplace and School Travel Plans. It was originally rolled out across all 33 London boroughs in 2005 and the web enabled version of iTRACE is now available to Local Authorities throughout the UK. Local Authorities currently using iTRACE include all 33 London boroughs, Wigan, Hampshire, Portsmouth, and Southampton, Milton Keynes, and Buckinghamshire councils.

### **A.2 iTRACE functionality**

iTRACE functionality can be broken down into two types based on the user login types. There are two types of user logins available in iTRACE.

- Government officer; and
- Site coordinator.

#### ***A.2.1 Government officer activities***

The government officer is responsible for entering data (except site audits and staff surveys) pertaining to a workplace or school. The main focus of the system is to store the results of site audits, staff surveys and targets for change. iTRACE also holds all the necessary site information such as contact details, business activity, site description, address and planning related information such as financial contributions and Section 106/278 details.

There are 11 workplace and 10 schools standard reports available to the government officer covering a variety of topics from project management e.g. 'Inspections Due' to performance monitoring 'Modal Shift':

The workplace reports include:

- Inspections Due;
- Modal Shift;
- Best Practice Ratings;
- Voluntary Targets vs Actuals;
- Planning Obligation Targets vs Actuals;
- Borough Targets vs Actuals Summary;
- Planning Status;
- Planning Obligation Contributions;
- Workplace Full Summary;

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<sup>4</sup> WESTTRANS is a partnership of the six West London boroughs of Ealing, Brent, Hammersmith & Fulham, Harrow, Hillingdon, and Hounslow, working with West London Business, West London Alliance, Park Royal Partnership and other key stakeholders towards a shared vision of transport policy, planning and delivery in West London.

- Travel Plan Report Template; and
- Travel Survey Summary Report.

The school reports include:

- Inspections Due;
- Modal Shift;
- Best Practice Ratings;
- Target vs Actuals;
- Planning Obligation Target vs Actual;
- Borough Ad-hoc Targets Summary;
- Borough Targets vs Actuals Summary;
- Planning Status;
- Contacts Report; and
- School Full Summary.

The government officers will also have access to the management suite of reports which includes 9 workplace and 7 schools reports. These reports are high level statistical reports which can be used to compare geographical areas.

The workplace management reports include:

- Government Officer Usage;
- Workplace Travel Plans;
- Employees Covered by Travel Plans;
- Travel Plan Best Practice Rating;
- Total Modal Percentage Change;
- Workplace Parking Provision;
- Percentage of Organisation with Facilities;
- Organisation listed by Land Use / Business Activity; and
- Workplace Audit Status.

The school management reports include:

- Government Officer Usage;
- School Travel Plans;
- Staff and Students Covered by Travel Plans;
- Travel Plan Best Practice Rating;
- Total Modal Percentage Change;
- School Parking Provision; and
- Walk to School Week.

iTRACE also provides a series of predefined search to allow users to access site details quickly. The map view also assists the users in locating the site in both terms of geographical location and proximity to other sites or travel infrastructure e.g. a rail station or cycle network.

### ***A.2.2 Site coordinator activities***

The site coordinator can, at the request of the Government Officer, complete an online site audit and a number of online or paper-based staff surveys.

Surveys included in the system are:

- Site Audit;
- Staff Survey;
- NHS Staff Survey;
- NHS Visitor Survey;
- Higher Education Staff Survey; and
- Higher Education Student Survey.

The site coordinator can have access to four different reports covering travel mode splits, survey statistics, and main method/home postcode which include.

- Travel Plan Report Template;
- Travel Survey Summary Report;
- Staff Postcode (CSV); and
- Mode of Transport Usage.

The Site Coordinator can also view current and historical site audits and staff surveys.