Preference Accommodating and Preference Shaping: Incorporating Traveler Preferences into Transportation Planning

by

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Abstract

This dissertation examines the psychological factors that influence travel behavior such as people's personality traits, environmental attitudes, car pride and perceptions of convenience and comfort. Despite the recognition of the importance of these psychological factors in better understanding travel behavior, transportation agencies have failed to integrate them into planning practice and policy debate in the quantitative way. This dissertation reflects on this failure, identifies the barriers that have contributed to it, and reviews innovations in travel behavior research which may help overcome these barriers.

This dissertation proposes a structure for analyzing traveler preferences that incorporates these psychological factors into travel behavior analysis. A set of eight factors are presented as the latent elements of travel preferences to illustrate the structure, including two personality traits; three environmental attitude factors and car pride; and two perceptual factors of convenience and comfort.

A MIMIC model quantifies the eight factors and examines the relationships among these factors as well as between them and socioeconomic variables. Despite the significant correlations with socioeconomic variables, personality, attitudes and perceptions prove to be characteristics of individuals that are distinct from the socioeconomics.

The dissertation presents three applications that incorporate these latent factors into travel demand analysis of three critical aspects of travel behavior: car use, mode choice and car ownership. Incorporating the latent variables significantly improves the overall exploratory power of the transportation models. The results suggest that plausible changes in traveler preferences can have an effect on behavior in magnitude similar to the impacts that result from rising household income or increased population density.

Unobserved heterogeneities exist not only for preferences with respect to observed variables such as travel time, but also for latent factors such as car pride and perception of convenience.

Mutual dependencies between travel preferences and behavior are identified and the direction and strength of the causal connections are modeled explicitly. Depending on the specific latent factors and aspect of travel behavior, the causal relationships could be from preferences to behavior, from behavior to preferences, or be significant in both directions concurrently

These three applications also demonstrate in terms of methodology that 1) hierarchical relationships among latent factors can be simultaneously estimated with discrete choice models; 2) latent variable and latent class modeling techniques can be combined to test unobserved heterogeneities in travelers' sensitivity to latent variables; 3) causal relationships between behavior and preferences can be examined in the SEM or hybrid SEM and discrete choice model.

This dissertation proposes two complementary perspectives to examine how to embed traveler preferences in the planning practice: planning as preference accommodating and planning as preference shaping. Combining both perspectives, this dissertation argues that by ignoring the importance of traveler preferences, not only may we make serious mistakes in the planning, modeling and appraisal processes, but we may also fail to recognize significant opportunities to mitigate or solve transportation problems by influencing and exploiting changes in people's preferences.

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When daner found baobei,

Both found home.

To Zhengzhen Tan

Contents

Abstract **2**

Acknowledgement **4**

Contents **6**

List of Figures **11**

List of Tables **13**

Chapter 1. Introduction **17**

1.1 Motivation 17

1.1.1 Travel behavior and social image concern 18

1.1.2 Travel behavior and environmental attitude 20

1.1.3 Significance to transportation planning and policy 22

1.2 Objectives 24

1.3 Research Approach 25

1.3.1 Overview of model systems 25

1.3.2 Choice of London 28

1.4 Thesis contribution 29

1.4.1 Behavioral findings on the impacts of psychological factors 29

1.4.2 A structure for analyzing traveler preference in transportation planning 30

1.4.3 Implementation of hybrid choice models based on generalized RUM framework 31

1.5 Thesis structure 32

Chapter 2. Literature Review **34**

2.1 Introduction 34

2.2 Travel Demand Theory 36

2.2.1 A brief history 36

2.2.2 Random utility maximization (RUM) 37

2.2.3 RUM assumptions 38
2.2.4 Contrasting economic and behavioral perspectives on preferences 38
2.2.5 Comparing models of consumer behavior 39
2.2.6 Latent constructs and their measurement 41
2.2.7 Dichotomy of internal preference and external environment 42
2.2.8 Synthesis 42
2.3 Statistical methods 44
2.3.1 Latent variable model 44
2.3.2 Latent class model 45
2.3.3 Structural Equation Modeling and its Application in Transportation 47
2.3.4 Integrated framework 56
2.3.5 Latest applications 58
2.4 Data 60
2.4.1 Conjoint analysis from market research 60
2.4.2 Psychometric data 61
2.5 Computation and Software 61
2.5.1 Simulation 61
2.5.2 Software development: 62
2.6 Summary 63
Chapter 3. A Proposed Structure for Analyzing Traveler Preferences ..65
3.1 A Structure for Analyzing Traveler Preferences 65
3.1.1 Categorization of the factors influencing travel behavior 66
3.1.2 Dichotomy between internal preference and external environment 67
3.1.3 Description of the eight latent factors 69
3.2 Data Source and Variable Definitions 71
3.3 Exploratory and Confirmatory Factor Analysis 75
3.4 Multiple Indicators and Multiple Causes (MIMIC) model 81

3.4.1 Model specification and estimation 81

3.4.2 Relationships between the SES variables and the latent factors 83

3.4.3 Interrelationships among the latent factors..... 86

3.4.4 Overall connection between latent factors and SES variables 87

3.5 Summary 87

Chapter 4. Traveler Preferences and Car Use.....89

4.1 Introduction 89

4.2 Mutual Dependencies between Preferences and Behavior 90

4.3 SEM Specifications with and without Feedback Loop 91

4.4 Regression Models without Latent Factors 95

4.5 Car Mode share and Environmental Attitudes 99

4.5.1 Model specification..... 99

4.5.2 Model identification..... 101

4.5.3 Estimation results 103

4.5.4 Preferred model specification 107

4.5.5 Interpreting the causality between environmental attitudes and car mode share 107

4.6 Car Mode share and Personality Traits..... 109

4.7 Car Mode Share and Car Pride..... 110

4.8 Different Roles of Latent Factors in Car Share and Frequency Models..... 112

4.9 Direct and Indirect Effects of the SES Variables on Car Mode Share 114

4.10 Summary 115

Chapter 5. Traveler Preferences in Disaggregate Mode Choice 117

5.1 Data Processing and Variable Definition 118

5.2 Baseline MNL Mode Choice Model..... 120

5.3 Mode Choice Models with Latent Variables..... 123

5.3.1 Model 2: Choice model with car pride 123

5.3.2 Model 3: Choice model with environmental attitude 128

5.3.3 Choice models with multiple latent variables: Model 4 132

5.3.4 Choice model with multiple latent variables in hierarchical relationship . 136

5.4 Modeling Unobserved Heterogeneity in Traveler Preferences with Latent Classes Models 139

5.4.1 Heterogeneity in the Sensitivity to Travel Time 142

5.4.2 Heterogeneity in the sensitivity to the perception of convenience 145

5.4.3 Class membership defined by latent variables 148

5.4.4 Combining latent class model and latent variable models 150

5.5 Summary 152

Chapter 6. Traveler Preference and Car Ownership 154

6.1 Car Ownership Literature 155

6.2 Car Ownership in London and Great Britain 157

6.3 Baseline MNL Models of Car Ownership 159

6.3.1 Data and variables 159

6.3.2 Car Ownership Model with SES Variables 160

6.3.3 Car Ownership Model with SES, Land Use and PT Access Variables 161

6.4 Incorporating Latent Factors into Car Ownership Model 162

6.5 Latent Class Models to Test Heterogeneity in Traveler Preferences 166

6.5.1 Heterogeneity in the Sensitivity to Car Pride 166

6.5.2 Heterogeneity in the Sensitivity to Convenience 168

6.6 Conclusion 169

Chapter 7. Summary and Conclusions 170

7.1 Summary of Behavioral findings 170

7.2 Hypothetical Scenarios of Preference Change 172

7.2.1 What if environmental attitudes continue to improve? 173

7.2.2 What if car pride becomes less important? 176

7.2.3 Summary of all scenarios 178
7.3 Policy Implications 178
7.4 Preference accommodating 180
7.4.1 Reflection on the four barriers 180
7.4.2 Implications for customer research 181
7.4.3 Implications for demand modeling 183
7.4.4 Implications on project appraisal 183
7.5 Preference shaping 185
7.5.1 Advantages of preference shaping 185
7.5.2 Concerns over preference shaping 186
7.5.3 Justification of democratic preference shaping 188
7.5.4 Practicality of preference shaping in transportation planning 190
7.5.5 Application example: STDM in Sutton, London 192
7.6 Limitations 193
7.7 Future research 194
7.7.1 Fill in the matrix 195
7.7.2 Identify the core 195
7.7.3 Track the dynamics and prepare for forecasting 196
7.7.4 Examine the triggers 196
7.7.5 Standardize the practice 197
7.8 Concluding remarks 198

Appendix A: Psychometric Indicators in the Londoner's Lifestyle and Car Dependence Survey 200

Appendix B: Speed Regression to Calculate the Travel Time for Alternative Travel Options 204

Bibliography 212

List of Figures

Figure 1-1 Interaction between transportation and climate change 21

Figure 1-2 Model System 25

Figure 1-3 Generalized Random Utility Model (Walker and Ben-Akiva 2002) 27

Figure 1-4 Dissertation Structure..... 33

Figure 3-1 Example structure of traveler preferences with eight latent factors..... 69

Figure 3-2 PTAL Map of Greater London, Source: Greater London Authority, 2003 74

Figure 3-3 Access Distance to Bus Stops, Tube and Rail Stations..... 75

Figure 3-4 Multiple Indicators and Multiple Causes Model (MIMIC) 82

Figure 3-5 Detailed Path Analysis Diagram..... 82

Figure 3-6 Standardized Coefficients between the Latent Factors in the PA Diagram 86

Figure 4-1 Path Diagram for the SEM model without Feedback Loop 93

Figure 4-2 Path Diagram for the SEM model with Feedback Loop..... 93

Figure 4-3 Path Diagram of the SEM Model without Feedback 100

Figure 4-4 Path Diagram of the SEM Model without Feedback 100

Figure 4-5 Partial Path Diagram among the Latent Factors 105

Figure 4-6 Full Path Diagram of the SEM model with Feedback Loop 108

Figure 4-7 Path Diagram for the Relationships between Personality and Car Mode Share 110

Figure 4-8 Path Diagram for the Relationships between Car Mode Share and Car Pride and Perceptions 112

Figure 4-9 Direct and Indirect Effects of having a bike on Car Mode Share..... 115

Figure 5-1 Path Diagram of the Latent Variable Choice Model..... 124

Figure 5-2 Path Diagram of the Choice Model with Multiple Latent Variables in Parallel 132

Figure 5-3 Comparison between MNL model, Latent Variable Model and Latent Variable Model with Hierarchical Relationship..... 136

Figure 5-4 Structure of Model 5: Latent Variable Choice Model with Hierarchical Relationship 137

Figure 5-5 Path Diagram of Latent Class Model 6 142

Figure 5-6 Comparison of Model 7 with a typical latent class model 146

Figure 5-7 Schematic Diagram of Latent Class Model 8 149

Figure 5-8 Schematic Diagram for Model 9 150

Figure 5-9 Full Path Diagram for Model 9 151

Figure 6-1 Car ownership by household income band (in thousand pounds) 158

Figure 6-2 Car ownership in London (1988-2007) 159

Figure 6-3 Car Ownership Model with Latent Variables without Feedback 163

Figure 6-4 Car Ownership Model with Latent Variables with Feedback 163

Figure 7-1 Distribution of the Probabilities of Owning 1 Car 175

Figure 7-2 Distribution of the change of probabilities in Scenario 1 175

Figure 7-3 Distribution of *f_CarPride* in scenario 2 176

Figure 7-4 Distribution of the change of probabilities in Scenario 2 177

List of Tables

Table 2-1 Travel Behavior Research in Economics and Psychology/Marketing Research 36

Table 2-2 Categorization of Consumer Models, Reproduced from Antonides (2008)..... 40

Table 3-1 Variables Influencing Travel Behavior 67

Table 3-2 Social Economic Status Variables..... 72

Table 3-3 Factor Loadings of the EFA for Attitudinal Factors 76

Table 3-4 Correlations among Environmental Attitude Factors..... 76

Table 3-5 Factor Loadings of the EFA for Personality Factors 77

Table 3-6 Factor Loadings of the EFA for Car Pride, Convenience and Comfort 78

Table 3-7 Factor Correlations 78

Table 3-8 Descriptions of Latent Factors and Number of Indicators..... 78

Table 3-9 Factor Loadings of the Confirmatory Factor Analysis..... 80

Table 3-10 Goodness-of-fit statistics for CFA model 81

Table 3-11 Goodness-of-fit statistics for MIMIC Model 82

Table 3-12 the Impacts of SES Variables on Personality Traits..... 83

Table 3-13 the Impacts of SES Variables on Attitudes..... 84

Table 3-14 the Impacts of SES Variables on Convenience and Comfort 85

Table 4-1 Model Variations..... 94

Table 4-2 Car mode share and trip frequency models with full sample 96

Table 4-3 Car mode share models for the full and car owner samples..... 98

Table 4-4 Car use frequency models for the full and car owner samples 99

Table 4-5 System Matrix for Model Specification 2..... 102

Table 4-6 Reduced Matrixes for Model Specification 2..... 102

Table 4-7 Goodness-of-fit statistics 104

Table 4-8 Structural equations for latent variables 106

Table 4-9 Structural equations for car mode share..... 107

Table 4-10 Goodness-of-fit statistics 110

Table 4-11 Goodness-of-fit statistics 111

Table 4-12 Overall Data Fit Comparison 113

Table 4-13 Significance of the Causal Links between Behavior and Preferences 114

Table 5-1 Summary of Models 118

Table 5-2 Goodness-of-Fit for Baseline MNL Model 120

Table 5-3 Baseline MNL Model Results 122

Table 5-4 Measurement equations for the car pride latent factor 124

Table 5-5 Structural equations for the car pride latent factor 125

Table 5-6 Choice Model with the Car Pride Latent Factor 126

Table 5-7 Goodness-of-Fit Statistics for Model 2 127

Table 5-8 Measurement equations for the environmental attitude latent factor 128

Table 5-9 Structural equations for the environmental attitude latent factor 128

Table 5-10 Choice model with the environmental attitude latent factor 131

Table 5-11 Goodness-of-fit Statistics for Model 3 132

Table 5-12 Measurement Equations for Latent Factors 134

Table 5-13 Choice Model with Multiple Latent Factors in Parallel 134

Table 5-14 Goodness-of-fit Statistics for Model 4 136

Table 5-15 Coefficients of the Path Analysis among Latent Factors 137

Table 5-16 Measurement Equations for Latent Factors 138

Table 5-17 Choice Model with Multiple Latent Factors and Hierarchical Relationship . 138

Table 5-18 Goodness of Fit Statistics for Model 5 139

Table 5-19 Summary of Goodness of Fit for Models 1 through 5 139

Table 5-20 Hypotheses tested through latent class and latent variable models 141

Table 5-21Coefficients that are common across classes 144

Table 5-22 Coefficients that differ across classes 145

Table 5-23 Binary logistic class membership model 145

Table 5-24 Class membership counts 145

Table 5-25 Coefficients that are the same across classes 147

Table 5-26 Coefficients that differ across classes 147

Table 5-27 Class membership model 148

Table 5-28 Class Membership Counts 148

Table 5-29 Measurement equations for the factor convenience 148

Table 5-30 Coefficients that differ across classes in Model 8 149

Table 5-31 Class Membership Model in Model 8 149

Table 5-32 Coefficients that differ across classes in Model 9 152

Table 5-33 Class Membership Model in Model 9 152

Table 6-1 Models of Car Ownership 155

Table 6-2 Car Ownership in London and the Rest of Great Britain 157

Table 6-3 Car Ownership in London by Household Size 158

Table 6-4 Estimation Result of Car Ownership Model 1 (Base=No Car) 160

Table 6-5 Goodness of Fit Statistics for Model 1 161

Table 6-6 Estimation Result of Car Ownership Model 2 (Base=No Car) 161

Table 6-7 Goodness of Fit Statistics for Model 2 162

Table 6-8 Goodness-of-fit Statistics for Three Model Specifications 164

Table 6-9 the Impacts of Latent Variables on Car Ownership 165

Table 6-10 the Impact of Car Ownership on Latent Factors 165

Table 6-11 Standardized Coefficients for the Connections between Latent Factors 166

Table 6-12 Goodness-of-Fit Comparison between Models 1, 2 and 3 166

Table 6-13 Coefficients that are the same across classes 167

Table 6-14 Coefficients that differ across classes 167

Table 6-15 Class Counts 167

Table 6-16 Coefficients that differ across classes 168

Table 6-17 Class Membership Model 168

Table 6-18 Class Counts 168

Table 7-1 Distributions of *f_EnvTax* in Scenario 1 174

Table 7-2 Change of Car Ownership Probability in Scenario 1 by Region 174

Table 7-3 Change of Car Ownership Probability in Scenario 2 by Region 177

Table 7-4 Summary of Scenarios 178

Chapter 1. Introduction

This dissertation examines the psychological factors that influence travel behavior such as people's personality traits, environmental attitudes, car pride and perceptions of convenience and comfort.

Despite the recognition of the importance of these psychological factors in better understanding travel behavior, transportation agencies have failed to integrate them into planning practice and policy debate in the quantitative way. This dissertation reflects on this failure, identifies the barriers that have contributed to it, and reviews innovations in travel behavior research which may help overcome these barriers.

This dissertation proposes a structure for analyzing traveler preferences that incorporates these psychological factors into travel behavior analysis and applies it to examine three aspects of travel behavior that are essential to transportation planning: car usage, mode choice, and car ownership. This dissertation proposes preference accommodating and preference shaping as two ways to embed traveler preferences within planning practice.

Section 1.1 presents two anecdotal examples that motivate this research; section 1.2 presents the three main research objectives; section 1.3 describes the research approach including the model system and choice of London as the case study; section 1.4 summarizes the thesis contributions and section 1.5 concludes with the thesis structure.

1.1 Motivation

Two anecdotes that the author encountered, when working for Transport for London (TfL)—London's transportation authority, have motivated this research. One is about travelers' social image, and the other is about people's environmental attitudes with respect to travel.

1.1.1 Travel behavior and social image concern

"A man who, beyond the age of 26, finds himself on a bus can count himself a failure."

--Lady Margaret Thatcher, 1986[1]

That idea seems to be supported by research. Grava (2002, p349) stated that buses appear to have a negative public image; many people seem to believe that their social status would be impaired if they were to be seen using a bus. Garrett and Taylor (1999) found that buses were used only by downtown commuters and what they called "transit dependents": people who were too young, too old, or too poor to drive, who lived in inner cities, had low incomes, and lacked access to cars. Hall (2007) also agrees that bus-based systems are perceived as unsexy and down-market. Grava (2002) went on to argue that such widely held perceptions are a most serious issue that threatens the basic viability of the bus mode.

Thatcher's words dramatized people's dislike of buses, which went beyond the physical aspects such as being slow and unreliable. Choices of travel mode were taken as part of the manifestation of people's social status or at least were perceived as such by some individuals.

Twenty years later, when the author worked in London between 2005 and 2007, and commuted on London buses and Underground, it seemed that people, rich and poor, young and old, traveled on the public transport system without real concern that their social reputation might be stained by traveling on buses, and never worrying that this behavior could be seen by others as implying they were failures. In fact in the fall of 2008, the Mayor of London sent London's iconic red double-decker buses to Beijing to receive the Olympic Flag that will fly over London in 2012, reflecting Londoners' pride in their buses.

[1] UK House of Commons Hansard Debates.
http://www.parliament.the-stationery-office.co.uk/pa/cm200203/cmhansrd/vo030702/debtext/30702-10.htm

To complete the picture, there was a phrase used to describe an ordinary Londoner around the dawn of the 20th century, and later used as a term in English law to refer to a reasonably educated and intelligent normal person—"The man on the Clapham Omnibus". It is intriguing to see that characterizing a person by the travel mode he chooses has long been recognized and embedded in the culture.

On the flip side, the status and identity associated with owning and riding a car are recognized as an important source of attraction to the car. From the very early days of motorization, being a car owner was an envied and respected position (Sandqvist 1997) and ever since the car has continued fulfilling the role of powerful status symbol (Garling and Loukopoulos 2008).

A seemingly mundane activity like selection of a daily travel mode may be strongly associated with one's social status. From "normal" to "failure" to "pride", Londoners' image of their buses has varied dramatically over the last century. This dissertation will argue that the sense of pride and social image concerns can have important impacts on travel mode choice, on perceptions and attitudes toward public transportation and ultimately on public transportation demand, above and beyond the impact of travel time and cost, the factors traditionally considered paramount in the transportation planning process.

However, transportation agencies seldom consider these factors in the planning process. Rarely are psychological factors such as personality traits, attitudes or perceptions included in the quantitative models of transportation demand analysis. For example, in the mainframe transportation models in Transport for London (TfL): LTS and Railplan, travel cost and time and socioeconomic characteristics remain the only factors that are considered to determine travel behavior. (Transport for London 2005a, LTS Technical Report, Transport for London 2005b Railplan Modelling User Guide)

In TfL's T2025 plan, the long term comprehensive transportation plan for 2025, even though such issues as enhancing the environment, tackling climate change and reducing social exclusion are emphasized as the key objectives of TfL, the impacts of these factors

on travel behavior have not been integrated into the quantitative models that underpin demand forecasting and planning (Transport for London 2006). In contrast to the careful documentation and quantitative modeling of the potential changes to the system such as the Cross-rail project and adjustment to the Congestion Charging zone, the psychological factors underlying traveler preferences continue to be ignored. Envisioning the future, we have only focused on half of the job. In most transportation agencies, the failure to consider these softer factors exists throughout the processes in which travel behavior is monitored, projects are appraised, future demand is forecast, service is planned, and customer research is conducted.

1.1.2 Travel behavior and environmental attitude

"How much CO^2 will I produce if I drive from West Hampstead to Canary Wharf? How much can I save if I take the Tube instead?"– a question posed by a flat mate in London, 2007

On average, traveling by car in London generates 110g of CO_2 per passenger kilometer travelled versus the Underground figure of 60g/km (Greater London Authority 2007, The Mayor's Climate Change Action Plan). So a person traveling 20km between West Hampstead and Canary Wharf could save 1kg of CO_2 by switching from car to the Underground.

Addressing the question in purely economic terms simply requires an estimate of pollution by different travel modes. But does it really matter to an individual if it is 1kg or 1.5kg CO_2 saved? Almost certainly not. There is a long way to go before someone can translate his individual 1kg of CO_2 daily emissions saving to global temperature impact or rising sea level or any other specific consequence, monetary or other, that may result. Most people have at best only a weak sense of the scale of CO_2 emissions and their impact on the environment.

However simple economic accounting trivializes the significance of the story. What matters most is that the question is being asked at all. Prior to industrialization, people

took pride in cutting down trees and building tall chimneys. Not until the late 1960s, did the natural environment become a subject of public policy debate or lay conversations.[2] Even since then, there has been more talk than action. But the latest Global Warming and Climate Change concerns seem to have awakened people's environmental conscience. Many may be starting to consider the consequences on the environment of their daily activities such as commuting mode choice and even to adjust their behavior accordingly. The environment is becoming a salient factor that enters people's calculus in travel mode choice.

In a recent UK Department for Transport evidence review of public attitude towards climate change and transportation behavior, Anable et al (2006) reported a higher level of awareness of the seriousness, scale and urgency of climate change. UK DfT (2008) reports a rather stable 80% of adults said they were very or fairly concerned about climate based on 2006, 2007 and 2008 surveys.

Furthermore, a majority of people recognize a link between climate change and transport specifically. UK National Statistic Omnibus Surveys in 2006, 2007 and 2008 reported that around 70% of the population identified transport as a cause of climate change.

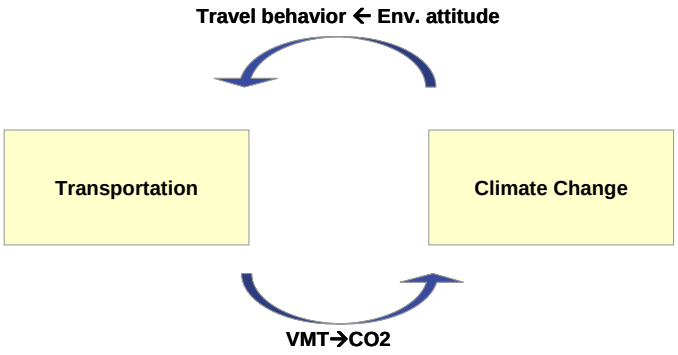


Figure 1-1 Interaction between transportation and climate change

[2] It was not until 1969 that the first major U.S. environmental legislation, the National Environmental Policy Act was passed by the Congress and the Environmental Protection Agency created.

In contrast to this societal trend of increasing attention to the environment, most transportation agencies have not seriously examined the impact of environmental attitudes on travel behavior. Most studies of this type have focused on the one-way link from transportation to global warming: transportation in the end boils down to vehicle mile travelled (VMT) and thus tons of CO_2 generated, and from that point on, it is no longer the transportation professionals' business. This thesis argues that the reverse direction link should also be considered: because of the climate change movement, people may change their environmental attitudes, adjust their travel behavior accordingly and influence the transportation system, as shown in the top arrow in Figure 1-1. Only when the influences of climate change on travel behavior through environmental attitudes are recognized, are transportation planners no longer just passive respondents to the climate change movement and can fully engage in the two-way dialogue between transportation and climate change.

1.1.3 Significance to transportation planning and policy

Just as London's transportation systems have changed over recent decades such as through bus quality improvement, network expansion and Congestion Charging, so have the way Londoners view these systems and make their travel choices. People's travel preferences are under continuous influences: business advertisements, political propaganda, peer pressure, education and cultural trends as well as open dialogue that engages public participation.

For example, Lyon et al (2008) stated that the most recent higher attention being given to climate change had happened quite swiftly and the current level of awareness of climate change and its connection to transportation contrasted significantly with surveys in the past few years. Take car pride as another example, Garling and Loukopoulos (2008) summarizes the evidence for the different emphasis on car as a status symbol now compared with the early days of motorization: the ubiquity of the car has led to it being perceived as an everyday tool, much like a refrigerator, and anyone not owning a car is perceived as being less well off.

Until recently, most travel behavior models have not considered these factors. They treat traveler preference as a black box and focus on the direct mapping between transportation system attributes and travel behavior. In contrast to the rather sophisticated theories established to model transportation systems, the structure of traveler preferences has been studied less and is not as well understood.

Consistent with the imbalance between research focused on transportation systems and that focused on traveler preferences, there exists more disparity in the transportation planning and policy practice: most agencies track the transportation system evolution and plan future changes reasonably well, but few concern themselves with possible traveler preference changes over time, even over the longer periods implied by 20~25 year plans and effectively treat traveler preference as fixed in their modeling and forecasting practice.

This dissertation argues that to understand travelers' preferences is as important for transportation planning and policy as to understand transportation systems, and considers two points of view in discussing traveler preferences in transportation planning:

A passive view regards transportation planning as preference accommodating: to respect people's preferences by matching what we assume about how people behave with how they actually behave. Transportation agencies need to fill the gap between the rich set of factors people consider in making their travel choices and the limited set that are incorporated into transportation models in order to make forecasts and project evaluation more realistic.

An active view regards transportation planning as including preference shaping. Transportation agencies often focus on influencing behavior by changing the physical systems, e.g., expanding the network by building Cross-Rail in London or altering the price structure by introducing Congestion Charging. The possibility of actively influencing traveler preferences through these psychological factors opens a whole new set of options that have been largely overlooked in the past.

Combining both perspectives enables us to position transportation policy within the broad context of sustainable metropolitan management. As global warming, energy security, and sustainability concerns pressure transportation planners to anticipate significant changes in urban activities and travel behavior, it is becoming increasingly important to understand their impacts on traveler preference, to consider preference shaping possibilities and to integrate their analysis into transportation models and policy discussions.

Back to the above examples, both the disassociation of travel mode choice from social image concern and the climate change movement awakening people's environmental consciousness can have profound impacts on travel behavior and suggest changes in traveler preferences over recent decades. But transportation agencies have not incorporated these factors into the planning process and implicitly assume traveler preferences to be fixed. This contrast motivates the dissertation.

1.2 Objectives

The dissertation aims to

1) Propose a structure for analyzing traveler preference that incorporates the psychological factors that influence travel behavior such as personality traits, environmental attitudes, car pride, and perceptions of convenience and comfort

2) Incorporate the psychological factors of traveler preferences into transportation models and examine their impact on three critical aspects of travel behavior: car use, mode choice and car ownership

3) Examine the unobserved heterogeneity in people's sensitivity to these psychological factors and introduce psychological factors in the segmentation of the population.

4) Suggest ways of better integrating traveler preference into transportation planning and argue for a balance of attention to traveler preferences and to transportation systems

1.3 Research Approach

Econometric models that combine discrete choice modeling and structural equation modeling techniques are the main method used to examine traveler preferences and incorporate them into transportation modeling and planning.

These econometric models are supplemented by descriptive statistics, anecdotes, literature review, and interviews. London is chosen as the study area for three reasons which will be discussed in section 1.3.2. The key data source is a cross-sectional household travel survey with psychometric indicators to measure attitudes and perceptions, described in chapter 3. Various observations about the planning practice in Transport for London came from interviews with TfL staff members.

1.3.1 Overview of model systems

The core of the dissertation includes four econometric models as shown in Figure 1-2

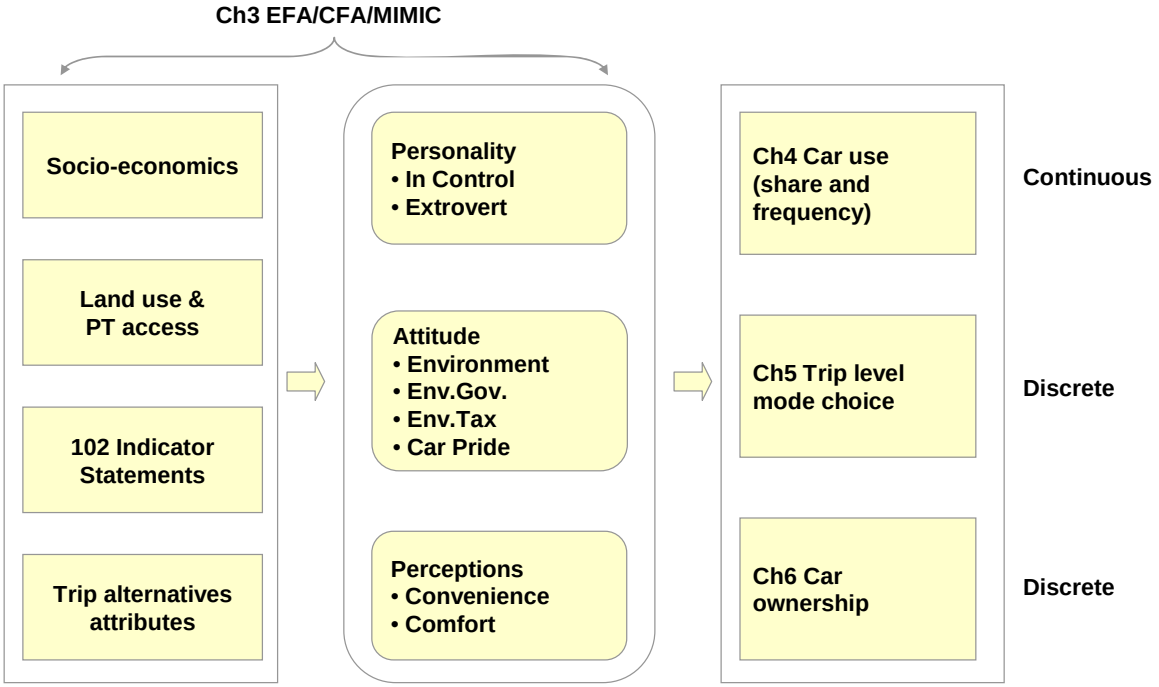


Figure 1-2 Model System

The left section of Figure 1-2 lists all the independent variables that are used in the models; the middle section shows the eight psychological factors that are identified and integrated into the travel behavior models; and the right section lists the three aspects of travel behavior examined in this dissertation.

A Multiple Indicators and Multiple Causes (MIMIC) model, described in chapter 3, integrates the Confirmatory Factor Analysis (CFA) model that abstracts eight psychological constructs into quantitative factors and the Path Analysis (PA) model that examines the interrelationships among these factors, between them and the socio-economic characteristics, land use and public transport access variables.

Chapters 4, 5 and 6 present three models demonstrate how the psychological factors can be incorporated into transportation models to examine their impacts on three aspects of travel behavior: car use at an aggregate level, mode choice at a disaggregate level, and car ownership.

An individual's travel decision can be generalized as a multi-stage process, the long-term decisions such as residential location, work location, and car ownership; and the short-term decisions such as choice of traveling or not, choice of travel mode, choice of departure time and choice of path. In theory, the psychological factors of traveler preferences should be and can be examined with respect to any of these decision stages but this dissertation chooses to model car use, mode choice and car ownership for two reasons:

1) These three aspects of travel behavior can be supported by the data available to the author

2) These three aspects are part of the most important travel-related decisions that collectively largely define the nature and scope of a city's transportation problem. They are also aspects of travel that transportation agencies can have relatively strong influence on, compared to, say, work place choice and residential location choice.

An individual's short-term decisions are assumed to be conditional on the long-term decisions. The aggregate car use model and disaggregate mode choice model in Chapter 4 and 5 are discussed given the level of car ownership. Chapter 6 examines the car ownership decision itself.

The discrete or continuous nature of the dependent variables entails different levels of difficulty in model specification and estimation:

1) The dependent variables in aggregate car use models are continuous. The models are estimated using classical Structural Equation Modeling (SEM) methods. Confirmatory Factor Analysis and Path Analysis are conducted simultaneously to obtain the estimation results

2) The dependent variables in disaggregate mode choice and car ownership choice models are discrete. Both models integrate the Discrete Choice Model (DCM) with the Structural Equation Model using the Generalized Random Utility Model framework (Walker and Ben-Akiva 2002, Figure 1-3). Latent variable and latent class modeling methods are used in the dissertation both separately and in combination.

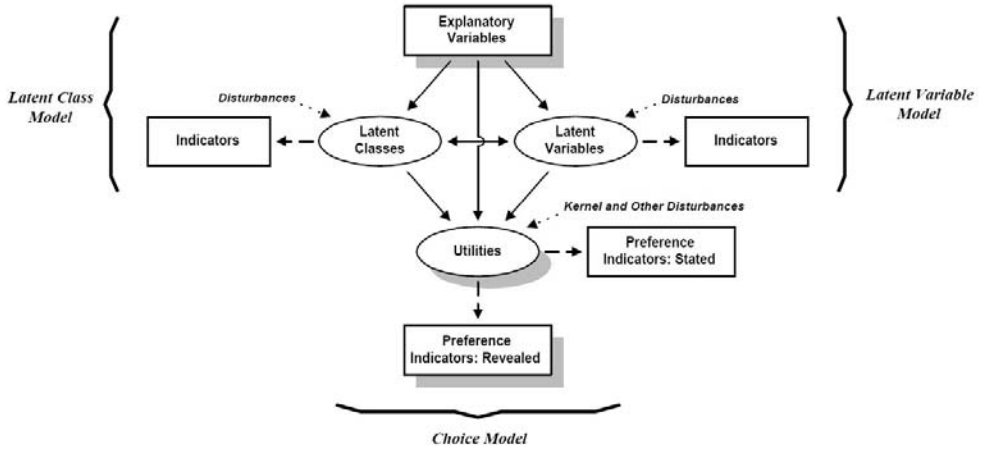


Figure 1-3 Generalized Random Utility Model (Walker and Ben-Akiva 2002)

Another important difference between the three models is the assumption on the direction of causality between travel behavior and psychological factors. Chapters 2 and

4 will discuss in detail the literature and methods to examine causality using structural equation modeling. The general assumption taken in this dissertation is in the short term, people's attitudes and perceptions influence travel behavior; and in the long term, in addition to the influence from attitude to behavior, the cumulative experience of travel behavior could also feedback and shape people's attitudes and perceptions.

Therefore in Chapters 4 and 6, both of which discuss the longer term travel behavior, aggregate car use and car ownership, the relationship between behavior and attitudes and perceptions are assumed to be bi-directional and the mutual dependencies between the two are explicitly tested. But in chapter 5, which examines the disaggregate mode choice, the relationship is assumed to be one directional from attitudes and perception to behavior.

1.3.2 Choice of London

London is chosen as the focus of the research for three reasons:

First, London concentrates several social trends that make the discussion of psychological factors more relevant. For example, London is where the past mayor commuted on the Tube and the current mayor rides his bike, while twenty years ago "a man who, beyond the age of 26, finds himself on a bus can count himself a failure"; it is one of the first cities to have implemented a climate change action plan and call for behavioral changes in everyone's daily life to address the climate change problem; and it is where bicycling is resurgent and heavily promoted as a fashionable life style, …

Second, Transport for London is experimental in implementing new ideas such as:

- Congestion Charging: it not only deters car use by directly increasing its cost, but more importantly, as David Begg, Chair of the Commission for Integrated Transport argues, the scale and political courage of the London initiative has achieved a psychological breakthrough resulting in a more informed and rational debate about car use and public transport (Begg 2003)

- Smart Travel Demand Management program: this program provides an example of influencing travel behavior though the psychological factors such as environmental consciousness

Third, two years of experience in London provided the author with a broad perspective on London's transport system, an opportunity to interact with both transport decision makers and common Londoners, and the access to the data and models used in this dissertation.

1.4 Thesis contribution

This dissertation contributes to the transportation planning literature in four respects:

1.4.1 Behavioral findings on the impacts of psychological factors

The dissertation presents a set of behavioral findings with respect to the psychological factors and their impact on travel behavior

- Eight psychological factors including personality traits, environmental attitudes, car pride, and perceptions of convenience and comfort can be measured effectively by the psychometric indicators
- These personality traits, attitudes and perceptions are characteristics of individuals distinct from their socio-economic status (SES) and SES variables only explain a minimal amount of the variation of people's personality, attitudes and perceptions. We need to develop separate measures for these dimensions
- Integrating these latent factors into travel behavior analysis significantly increases the explanatory power of the models, provides more realistic description of travelers' decision making, and expands the range over which transportation models can inform policy debates and planning decisions
- The eight latent factors play distinct roles in explaining these different aspects of travel behavior: car use vs. car ownership; aggregate vs. disaggregate mode choice; and relative car mode share vs. absolute car use frequency.

- The impact of certain socio-economic and demographic variables on travel behavior changes significantly after latent variables are introduced. Direct and indirect effects of socio-economic and demographic variables on travel behavior are distinguished through the introduction of latent variables
- Unobserved heterogeneities exist not only for preferences with respect to the observed variables, but also to the latent factors such as car pride and perception of convenience

1.4.2 A structure for analyzing traveler preference in transportation planning

The dissertation proposes a structure for analyzing traveler preferences that incorporates psychological factors as well as socioeconomic and demographic characteristics.

This analysis structure helps systematize the policy variables already being examined within planning agencies, clarify their interrelationships and identify holes in the structure that occur in current planning practice. This structure also highlights the need to bring knowledge from multiple disciplines: economics, psychology, sociology and other social sciences to enhance our understanding of traveler preferences.

The dissertation argues for attention to the psychological factors of traveler preferences at a similar level to the transportation systems in transportation planning, and presents two perspectives on how to examine traveler preferences in transportation planning: preference accommodating and preference shaping.

The preference accommodating and preference shaping perspectives can be applied throughout the planning processes including travel behavior monitoring, project appraisal, demand forecasting, transport service planning, and customer research.

A significant opportunity to solve transport problems emerges from better understanding traveler preferences and actively influencing changes in traveler preferences, which could be cost-effective compared with infrastructure investment or

could enhance their impact. This research suggests a need to rethink the balance between our efforts and investments targeted at improving the physical transportation system and those targeted at accommodating and/or influencing people's preferences.

1.4.3 Implementation of hybrid choice models based on generalized RUM framework

Walker and Ben-Akiva (2002) recognized the need for more applications to test the generalized framework in different contexts. This dissertation presents a series of hybrid choice models that apply this framework to different aspects of travel behavior. Two implementations are new to the existing applications:

(A) Preserve the interrelationships among latent variables in a hybrid SEM and choice model

In typical latent variable models, latent variables enter the utility function in parallel at the same level. This dissertation implements models that preserve the hierarchical interrelationships among latent variables and recognizes that some latent variables can enter the utility function directly while others enter indirectly.

(B) Implement choice models with latent variables and latent classes simultaneously

In most empirical applications, latent variable and latent class models are implemented separately. This dissertation presents three model variations in which latent variables and latent classes are implemented simultaneously to test different behavioral hypotheses:

1) People’s sensitivities to latent constructs vary across latent classes: for example, car pride is implemented as a latent variable, and travelers’ sensitivity to car pride can differ across classes.

2) People’s class membership can be influenced by their latent psychological traits. Latent class membership is usually defined by socio-economic characteristics in typical

latent class models. This dissertation implements models in which latent class membership is defined by latent variables as well as socioeconomic status variables. For example, people's personality such as "being extrovert" can be used together with income, age, and gender to define class membership.

3) The above two cases combined: people's sensitivity to latent constructs varies across classes which are defined by other latent constructs. For example, Chapter 5 uses this specification to test the hypothesis that people with greater car pride are more likely to give greater weight to the perception of convenience in the context of mode choice.

1.5 Thesis structure

The dissertation is organized as follows (see Figure 1-4):

Chapter 2 identifies four barriers that have prevented transportation agencies from considering psychological factors in planning practice: behavioral theory, statistical methods, data, and computation and software. It then reviews the literature on the latest innovations that help reduce each of the barriers and therefore enables the integration of these factors into transportation planning.

Chapter 3 proposes a structure for analyzing traveler preferences and presents the Multiple Indicators and Multiple Causes (MIMIC) model to quantify eight latent factors of travel preferences, and examine the interrelationships among them and with socioeconomic characteristics.

Chapter 4 presents a series of Structural Equation Models to examine the impact of psychological factors on individuals' car mode share and car use frequency, which are traditionally modeled as influenced principally through socioeconomic status, land use patterns and public transport accessibility.

Chapter 5 implements a hybrid structural equation and discrete choice model with simultaneous latent variable and latent class components to examine the latent factors'

impact on travel mode choice at the disaggregate trip level, and the unobserved heterogeneity of latent traveler preferences.

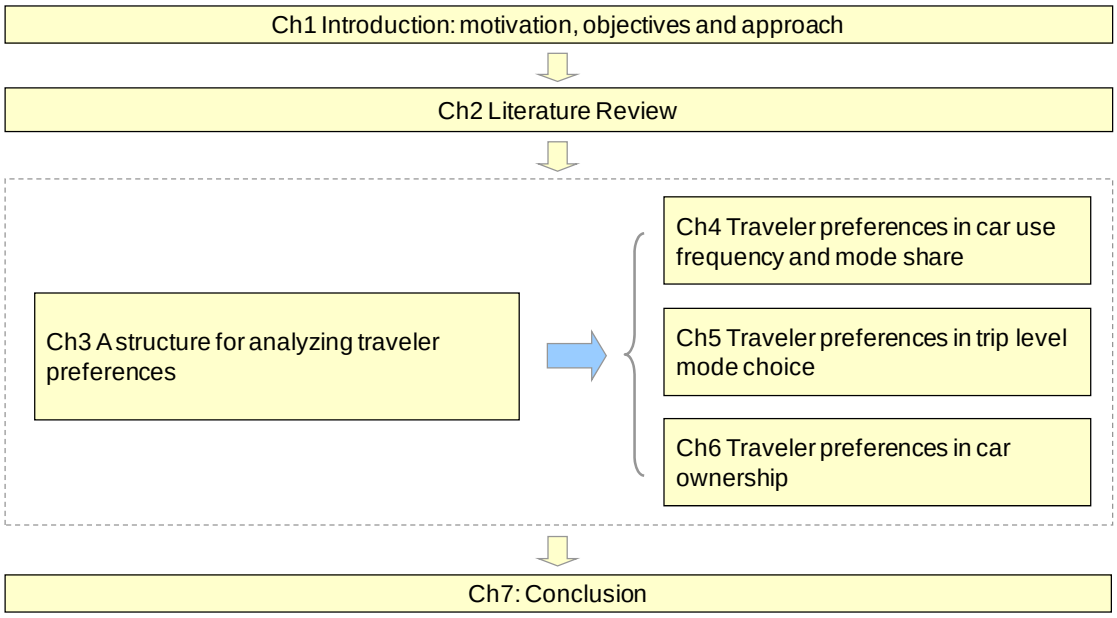


Figure 1-4 Dissertation Structure

Chapter 6 examines car ownership, compares the models with and without latent factors and examines heterogeneity in people's preferences for car ownership.

Chapter 7 summarizes the findings from chapters 3 through 6, discusses their policy implications and suggests directions for future research.

Chapter 2. Literature Review

2.1 Introduction

Chapter 1 discussed the need to incorporate traveler preferences, particularly their psychological elements, into transportation planning, as well as the failure of most transportation agencies to do so. This chapter reviews the literature to examine why this has been the case and how the situation is changing thanks to recent developments in theory and methods.

There are at least four barriers that have prevented transportation agencies from considering psychological factors in transportation planning:

(A) Travel Demand Theory

Most quantitative tools in transportation agencies are developed based on the classic economic theory of consumer behavior, which by and large ignores psychological factors. Psychological theories are known to transportation planners and do enter some of the qualitative discussion, but they are often regarded as too soft and intangible to be included in the quantitative analysis.

(B) Statistical methods

The statistical methods available to transportation agencies are not capable of handling psychological factors such as attitudes and perceptions or dealing with the complex model structures that are required to incorporate these factors into travel demand modeling. When psychological factors are analyzed, the methods usually do not go beyond univariate histograms or cross-tabulation with socio-economic variables.

(C) Data

The main data sources for travel demand analysis are household travel surveys and on-board travel surveys. Most of these surveys include a travel diary and questions

about the socio-economic and demographic characteristics of the individual and household. Until recently, psychological factors were rarely collected systematically in these travel surveys. One exception is the customer satisfaction survey, which are conducted in many transportation agencies on a regular basis. But even when these psychological surveys are conducted, the survey results are not integrated into mainframe transportation models and therefore do not play an effective role in travel demand analysis.

(D) Software and computation

To analyze psychological factors and integrate them into travel demand analysis often requires heavily involved coding in statistical software such as GAUSS and Matlab. It is a daunting task for most transportation planners unless trained in econometrics and programming. Compared to typical transportation demand models, the technical requirements to integrate psychological factors are much more demanding. Software packages that can facilitate the process by bypassing the technical details and allow users to operate at a high level are essential if the methods are to be widely implemented in transportation agencies.

In the past two decades, there have been substantial innovations in travel behavior research that can reduce each of these barriers and make it possible, though still not straightforward, to start incorporating these psychological factors into the transportation planning process. The main body of the literature review is dedicated to these specific developments, which follows two threads of development: economics and psychology and marketing research as shown in Table 2-1.

Table 2-1 Travel Behavior Research in Economics and Psychology/Marketing Research

	Economics	Psychology / Marketing Research
Theory	Theory of Consumer Behavior Random Utility Maximization (RUM)	Psychology of Behavior
Methods	Discrete Choice Analysis	Structural Equation Modeling (SEM) including Factor Analysis, Path Analysis, Multiple Indicators Multiple Causes Model (MIMIC)
Data	Revealed Preference (RP)	Stated Preference (SP) Conjoint Analysis Psychometric data
Software	Biogeme / Alogit	Amos / LISREL / Mplus

Section 2.2, 2.3, 2.4 and 2.5 will discuss, in order, innovations in decision theory, in statistical methods, in data collection and in software and computation. Section 2.6 concludes.

2.2 Travel Demand Theory

2.2.1 A brief history

Until the 1960s, the dominant tool for travel demand analysis was the gravity model, which described aggregate traffic between origin and destination zones in terms of zonal attraction and generalized cost. Meyer and Straszheim (1970) summarized this basic framework for transport demand analysis. The model was reasonably successful in describing highway flows but encountered major challenges when dealing with mode split, particularly dealing with public transportation, and did not consider traveler heterogeneity at all.

Born in 1970s, disaggregate behavioral travel demand analysis based on random utility maximization (RUM) has been the most widely used approach since then. This method forms components of both traditional four step models and the newer activity-based models. It is used in both short-term decisions such as mode choice, route choice, and

departure time choice, and in long-term decisions such as car ownership and residential location. (Ben-Akiva and Lerman 1985, McFadden 2000)

More recently, partially as a result of criticism of its lack of behavioral realism (Garling et al 1998, McFadden 1999), the RUM based transportation models have started to draw on findings from sociology, cognitive psychology, and marketing research (McFadden 2007). There is a diversity of efforts in the different direction of enriching the travel demand models (see Adamovwicz 2008, Ben-Akiva et al 2002 for a summary). This review will focus on the methods of measuring psychological factors such as perceptions and attitudes and incorporating them into model specification and estimation.

2.2.2 Random utility maximization (RUM)

Many statistical methods have been developed to model travel mode choice but the standard tool is the discrete choice analysis based on random utility maximization (RUM) theory. Discussions of the economic and psychological groundwork can be found in McFadden (1973), Manski (1977) and Ben-Akiva and Lerman (1985).

The model postulates that individuals derive utility by choosing an alternative that maximizes their utility. Since the utilities are unknown to the researchers, they are treated as random variables. More specifically, the random utility of an alternative can be expressed as a sum of an observable component (i.e. measurable or systematic term) and an unobservable component (i.e., random or error term). The observable component includes attributes of alternatives and characteristics of individuals. The random component includes four sources of uncertainty as identified by Manski (1977): unobserved alternative attributes, unobserved individual characteristics, measurement error and instrumental variables.

A class of probabilistic choice models can be constructed by appropriate specifications of the joint density of the error terms. For example, if the error terms are assumed to be independently and identically distributed Gumbel across alternatives and individuals, we obtain the choice probability as a closed-form expression known as the Multinomial

Logit Model (MNL), which is the most widely used model form. Other assumptions of the distribution of the error terms lead to various choice models such as probit, nested logit, and cross-nested logit. For a more extensive discussion, see McFadden (1984) or Ben-Akiva and Lerman (1985).

The outputs of the models are the probabilities of an individual choosing each alternative. These individual probabilities can then be aggregated to produce forecasts for the population.

2.2.3 RUM assumptions

The RUM models have their foundations in classic economic consumer theory, which is the source of many important assumptions for the models. The central assumption is the rationality assumption, which McFadden (1999) categorized into three types: perception-rationality, preference-rationality and process rationality. Simply put, economic theory assumes that people are rational agents with stable preferences who are able to collect all the necessary information, calculate the utilities from various outcomes and choose the one with maximum utility. An important feature of the theory is the consumer sovereignty property that preferences are predetermined in any choice situation, and do not depend on what alternatives are available. Succinctly, desirability precedes availability. (McFadden 2001)

These assumptions generated debate on the validity of such models but also fueled enthusiasm for revisions and extensions. Summarized below are two contrasting views of the way individuals make choices and the corresponding interpretations of preferences (Adamowicz et al 2008), and the alternative models of consumer behavior based on these two points of views.

2.2.4 Contrasting economic and behavioral perspectives on preferences

One common view among economists is that well-defined preferences exist for most objects, and that each individual has stable and coherent preferences (Rabin 1998). Further it is often assumed that people know their preferences, that they have the

ability to compute and identify the option that maximizes expected value, and that they will choose accordingly (Payne et al 1999). Under such assumptions, the task is to uncover (reveal) these well-defined preferences that may be hidden but are assumed to exist and the primary focus is on the mapping from information inputs to choice. Preferences can be treated for most economic applications as primitives of the analysis, and the decision process as a black box. This perspective leads to the assumption that consumer's choice making is consistent with the random utility maximization (RUM) theory (McFadden 1999).

An alternative viewpoint is behavioral and psychological and argues that preferences are generally constructed—not revealed—at the time of decision-making, based on contextual factors (Slovic 1995). The constructive perspective assumes that people do not have existing well-defined values for many objects; that facing a choice, they will selectively use information from the immediate task description as well as information from memory to construct a response on the spot; that preferences are not necessarily generated by applying an invariant expected utility maximization; instead, a wide variety of heuristics may be used to construct a preferential response (Simon 1955, 1990, Loewenstein 2001, Prelec 1991).

In psychological theories of the choice process, the individual is less organized, and more adaptive and imitative, than in the economists' standard model. Psychological descriptions of decision-making are both colorful and intuitive. Attitudes play a major role in determining how consumers define the decision-making task. In the words of Daniel Kahneman (1997), "Economists have preferences; psychologists have attitudes."

2.2.5 Comparing models of consumer behavior

Following these contrasting views of the decision making process, different models of consumer behavior have been developed. Stanovich and West (2000) distinguished between System I and System II types of decision making: System I is characterized by intuitive, largely unconscious, associative, automatic, heuristic and emotional decision processes, whereas System II is controlled, rule-based, systematic and analytic in nature.

Antonides (2008) applies this typology to organize the models into System I models, System II models and mixed-type models, a perspective which is adapted here in Table 2-2.

Table 2-2 Categorization of Consumer Models, Reproduced from Antonides (2008)

Types	Models	Concepts
System I Models	Heuristics	Simplified judgments Mental accounting Focusing on easy-to-evaluate attribute
	Loss Aversion	Asymmetric risk preference Endowment effect Status quo effect Sunk cost effect
	Subjective discounting	Hyperbolic discount rates
	Psychophysics	Psychophysical laws Probability weighting
	Learning by conditioning	Conditioning Development of preferences
	Other processes	Motivation, values, lifestyles Perceptions Other types of learning
System II Models	Demand Theory	Engel Curve Price Elasticity /Income Elasticity Hedonic pricing
	Life cycle model	Consumption and saving Wealth management
	Consumer Expectations	Consumer confidence Product expectations Customer satisfaction
	Theory of Planned Behavior	Attitudes, Social Norms, Perceived Behavioral Control, Intention
Mixed Type	Heuristic-Systematic Model Cognitive-Experiential Model Affective-Analytic Model	Information need Conditions for information processing

The economic models within System II are considered the most traditional types. They capture broad systematic relationships between income, price, alternative attributes, etc and choice behavior, assuming rule-based analytic decision making. They are widely used in transportation planning and policy making. New developments in such models,

however, frequently borrow concepts and insights from models in System I, such as incorporating latent constructs and their measurement into standard economic theory.

2.2.6 Latent constructs and their measurement

In behavioral and social sciences, there are hypothetical constructs conceived by an analyst with the intention of comprehending some research area of interest, for which there exists no operational methods for direct measurement. Although latent constructs are not observable, one can hypothesize that their effects on measurable variables are observable.

Latent constructs occur in many areas; for example in psychology, intelligence and verbal ability and in sociology, ambition and racial prejudice. The observed variables, which are considered to be manifestations of the underlying latent construct, are called indicators.

Psychometricians have pioneered the use of psychometric data, such as answers to survey questions regarding attitudes, perceptions, motivations, intentions, etc. The most well-known method for investigating the latent construct with a set of indicators is factor analysis (Gorsuch 1983, Morrison 1990) including both exploratory factor analysis (EFA) and confirmatory factor analysis (CFA):

Exploratory factor analysis (EFA) seeks to uncover the underlying structure of a relatively large set of variables. All of the indicators are allowed to be correlated with every factor in EFA and the researcher has no direct influence on the correspondence between indicators and factors, hence the term “exploratory”. There is no prior theory in EFA. Instead, one uses factor loadings to intuit the factor structure of the data.

Confirmatory factor analysis (CFA) seeks to determine if the number of factors and the loadings of indicators on them conform to what is expected on the basis of pre-established theory. Indicator variables are selected on the basis of prior theory and factor analysis is used to see if they load as predicted on the expected number of factors.

The researcher seeks to determine, for instance, if measures created to represent a latent variable really belong together. (Kline 2005)

Because of the factor analysis measurement, the latent constructs are also called latent factors, or factors. In this dissertation, latent constructs, latent variables, latent factors or factors are used interchangeably.

2.2.7 Dichotomy of internal preference and external environment

Simon (1956) in his classic paper "rational choice and the structure of the environment" distinguished the characteristics of environment that are external to a decision making organism from the preference, goals, needs and capacity that are internal to the organism. Simon then constructed a choice mechanism that an organism can employ to achieve its goals (for example, survival) facing the conditions in the external environment.

Chapter 3 will follow this concept, by distinguishing the internal traveler preferences from the external transportation system, and regarding consumer travel behavior as a function of the two. This is a customer-centric approach in which "internal" and "external" are defined from the viewpoint of the customer. It is different from the commonly assumed transportation-agency-centric viewpoint.

Even though it has long been debated to what extent the external environment can be distinguished from internal preferences, making this dichotomy clear could encourage planning agencies to recognize the importance of both influences and strike a balance between their interest in traveler preferences and the transportation systems themselves.

2.2.8 Synthesis

On one hand, these two viewpoints do not seem to be converging (Adamowicz et al 2008). Behavioral scientists have focused on demonstrations of how the assumptions of standard economics models often fail or why the decision processes are far from those

assumed in standard theory (Loewenstein 2001); Economists usually aim to accommodate the observed anomalies by specifying more general models and allowing for more latent factors in choice processes. In brief, a grand unifying theory is not at hand.

The reality of which viewpoint to take depends on the objectives: prediction or understanding:

- Economists focus on prediction and believe that perception, construal, and cognitive processes are well approximated by the Random Utility Maximization (RUM) models, i.e. regular systematic effects dominate. RUM models are the tool for organizing and approximating choice behavior, which capture enough of the systematic variance in order to measure preferences and evidence the changes (McFadden 2002).

- Psychologists focus on understanding and emphasize the complex and idiosyncratic features of choice behavior in order to illuminate deconstruction of the choice process. This view does a better job of understanding the preference changes and how to manage and influence them.

On the other hand, it may be healthy for each discipline to continue to evolve on its own path and borrow from the other to enrich itself. The economic and psychological choice theories are not antithetical but they can be utilized in conjunction with developments in psychometrics and econometrics to advance a richer class of choice models. (Gopinath 1995) This is the path that most transportation modelers are following: to build on the simplicity and elegance of economic theory and incorporate the key psychological factors which endeavor to explain and quantify seemingly irrational or inconsistent behavior.

As McFadden (2000) foresaw about the future of behavioral travel demand analysis:

“The standard RUM model, based on a mildly altered version of the economists’ standard theory of consumer behavior that allows more sensitivity of perceptions and preferences to experience, augmented with stated preference, perception, and attitude

measures that uncover more of the process by which context molds choice, will increasingly become the dominant methodology for behavioral travel demand analysis."

McFadden also acknowledges that the weak links in this setup are the lack of reliable scales for stated preferences, perceptions, and attitudes, and reliable mappings from experience and information to perceptions and attitudes. It would be useful to have a comprehensive research effort that identified the attitudes that are most relevant to travel behavior, and devised reliable methods for scaling these attitudes and relating them to experience.

2.3 Statistical methods

Two lines of statistical methods have been developed: one following the discrete choice analysis method, and the other following the structural equation modeling method. Four specific statistical innovations within the two lines of development are particularly relevant to this dissertation:

1) Latent variable models allow the psychological constructs to be modeled as latent variables and measured by multiple indicators

2) Latent class models allow the examination of the unobserved heterogeneity in traveler's responses to these psychological factors

3) Structural Equation Models (SEM) permit the examination of the interrelationships among the latent factors and between the latent factors and the socio-economic status

4) An integrated framework is developed to combine all these elements and allow the specification of these relationships and the simultaneous estimation of the full information model.

2.3.1 Latent variable model

A general approach to synthesizing models with latent variables and psychometric-type measurement models has been developed by Joreskog (1973), Wiley (1973) and Bentler

(1980). Specifically these models assume that the indicators are continuous, and the relationships between the observed and latent variables are linear. Such a model consists of two parts: a measurement model and a structural model. The first part specifies how the latent variables are related to the indicators, and the second specifies the relationship among the latent variables. Such models are widely used to define and measure unobserved factors in psychology, sociology and economics. The linear latent variable model is popularly referred to as the LISREL model. The socio-economic status variables can also be introduced into the structural part of the model to produce the Multiple Indicators Multiple Causes (MIMIC) model.

Recent developments (Ben-Akiva, Walker et al 2002; Ben-Akiva et al. 1994; Morikawa et al, 1996; Ben-Akiva, Walker et al 1999; Morikawa et al 2002; McFadden 1986; Ashok et al 2002; Vredin Johansson, Heldt, and Johansson 2006; Temme et el 2008) have advanced ways to make use of psychometric indicators and explicitly treat latent constructs such as attitudes and perceptions in discrete choice models to provide more behaviorally realistic descriptions of travel decision making. These developments will be discussed in Sections 2.3.4 the integrated framework.

2.3.2 Latent class model

Traveler behavior heterogeneity is well recognized by transportation planners. Some people value travel time more than others; some pay more attention to the environmental consequences of transport options; some are more sensitive to social image; some prefer more convenient options than faster options, etc.

To model heterogeneity in travel behavior across individuals has been one of the key areas of enhancement to discrete choice models. Traveler behavior heterogeneity includes both observed heterogeneity and unobserved heterogeneity, which impose very different levels of complexity on the model:

Observed heterogeneity may be incorporated in mode choice models by introducing individual socio-economic and demographic characteristics in the systematic portion of

the utility function and interacting level-of-service variables with these individual characteristics or segmenting the market with multiple-group analysis.

Unobserved heterogeneities may result from unobserved decision protocols, unobserved choice sets, unobserved taste variation, and unobserved attributes (Gopinath 1995). Two key techniques have been advanced to account for the unobserved heterogeneity in choice models: the latent class model (finite mixture model) and the random coefficient model such as the mixed logit model. A recent study by Greene and Hensher (2003) compared the latent class choice model with the mixed logit model in an example of drivers' road type choice in New Zealand and argued that each model has its virtues and limitations.

This dissertation chooses to apply the latent class model because of the following two advantages over the mixed logit model: 1) unlike the mixed logit model, the latent class choice model does not require the analyst to make a specific assumption about the distribution of parameters across individuals; and 2) the latent class choice model explicitly links preference heterogeneity to socioeconomic and demographic characteristics.

Latent class models can be used to capture unobservable segmentations in the population regarding tastes, choice sets, and decision protocols (Gopinath 1995). The concept of discrete mixing of functions (finite mixture models) has been around for a long time. For example, Lazarsfeld and Henry (1968) used latent class analysis to formulate latent attitudinal variables from dichotomous survey items. (See McLachlan and Peel 2000 for a review).

Later latent class analysis was introduced to choice models by Gopinath (1995), Bhat (1997), Swait (1994), Ben-Akiva and Boccara (1996). Gopinath (1995) provided a comprehensive treatment of latent class models in the choice context and applied it to travel demand analysis including modeling intercity travelers' mode choice allowing for different decision protocols among classes, and modeling shippers' choices between train and truck allowing for different sensitivities to time and cost. Ben-Akiva and

Boccara (1996) modeled commuters' mode choice allowing for different choice sets among travelers.

Also in the marketing research context, the latent classes are typically interpreted as market segments (Dillon and Kumar 1994; Wedel and Kamakura 1998). The same principle holds that the overall population is comprised of a mixture of heterogeneous subgroups each of which consists of similar individuals.

2.3.3 Structural Equation Modeling and its Application in Transportation

Compared to discrete choice models, Structural Equation Modeling (SEM) is less familiar to transportation planners so a lengthier introduction is provided. The outline in Golob (2003) is employed here to organize the introduction, including an overview, distinction between direct and indirect effects, testing causality using SEM, history of development, specification and identification, estimation, assessing goodness-of-fit, and a few applications to transportation planning.

(A) SEM overview

Structural equation modeling (SEM) is a statistical technique for testing and estimating causal relationships using a combination of statistical data and qualitative causal assumptions. Structural equation modeling (SEM) grows out of multiple regression but is more powerful way, taking into account the modeling of interactions, correlated independent variables, measurement error, correlated error terms, latent independent variables each measured by multiple indicators, and latent dependent variables measured by multiple indicators. (Textbooks on SEM include Bollen 1989, Kaplan 2000, Kline 2005, and overviews of the state of the method can be found in Cudeck et al 2001, Joreskog 1990, Mueller 1997)

An SEM with latent variables is composed of up to three sets of simultaneous equations: (1) a measurement sub-model for the endogenous (dependent) variables, (2) a measurement sub-model for the exogenous (independent) variables, and (3) a structural sub-model that captures the causal influences (regression effects) of the exogenous

variables on the endogenous variables and the causal influences of endogenous variables upon each other. All three sets of equations are estimated simultaneously. An SEM can have any number of endogenous and exogenous variables.

An SEM measurement model is used to specify latent variables as linear functions of other observed variables (indicators) in the system. As in CFA, in SEM the modeler specifies a priori the relationship between the factors and the associated indicators by deciding which of the parameters defining the factors are restricted to be zero, and which are freely estimated. In addition, one can constrain certain parameters to be equal to each other or to some non-zero constant. One can also specify non-zero covariances among the error terms of both the observed and latent variables. Specification of each parameter allows the modeler to conduct a rigorous series of hypothesis tests regarding the factor structure. Because there can be a large number of possible combinations in a measurement model with more than just a few variables, exploratory factor analysis (EFA) is sometimes used to guide construction of an SEM measurement model.

SEM includes as special cases multiple regression, simultaneous equations, path analysis, factor analysis, time series analysis, and analysis of covariance:

- Simultaneous equations and path analysis are special cases of SEM without measurement models but with observed variables
- Ordinary multiple linear regression is an SEM without measurement models but with one observed endogenous variable and multiple observed exogenous variables
- Confirmatory factor analysis is an SEM with only measurement models
- SEM with both measurement and structural models is known as SEM with latent variables

(B) Direct and indirect effects

An important distinction in SEM is between direct effects and indirect effects. Direct effects are the links between a cause variable and an effect variable. Each direct effect corresponds to an arrow in a path (flow) diagram. An SEM is specified by defining which direct effects are present and which are absent. With most modern SEM software this can be done graphically by manipulating path diagrams. The indirect effects between two variables are the effects along the paths between the two variables that involve intervening variables. Total effects are defined to be the sum of direct and indirect effects. The total effects of the exogenous variables on the endogenous variables are sometimes known as the coefficients of the reduced form equations.

(C) Testing causality using SEM

One advantage of SEM is its capacity to test different hypotheses of the causal relationships among variables. For example attitudes could either cause or be caused by behavior. In fact causality from both directions can exist concurrently (Dobson et al 1978).

Many studies have applied SEMs to examine a series of causal relationships in the transportation field, say, between car ownership and distance traveled (Den Boon 1980), between car ownership, season ticket ownership and modal usage (Axhausen et al 2001), between mode choice behavior and attitudes (Tardiff 1976), between mode choice behavior and support for policies that benefit the environment (Golob and Hensher 1998), and between acceptance of road pricing, intention to reduce car use and feelings related to fairness and freedom (Jakobsson et al 2000).

(D) History of development

Bollen (1989) proposed that SEM is founded on three primary analytical developments: 1) path analysis, 2) latent variable modeling, and 3) general covariance estimation methods. Below are the main contributions of each of these three areas.

1) Path analysis, developed by geneticist Sewall Wright (1934), introduced three concepts: (1) the first covariance structure equations, (2) the path diagram or causal graph, and (3) decomposition of total effects between any two variables into total, direct and indirect effects. Sociologists Blalock (1961), Boudon (1965), and Duncan (1966) discovered the potential of path analysis to test the alternative causal relationships. Modern SEM still relies on path diagrams to express what the modeler postulates about the causal relationships that generate the correlations among variables.

2) The development of models in which inferences about latent variables could be derived from covariances among observed variables (indicators) was pursued in sociology during the 1960s (Blalock 1963). These latent variable models contributed significantly to the development of SEM by demonstrating how measurement errors (errors-in-variables) can be separated from specification errors (errors-in-equations).

3) Joreskog (1967, 1969) developed the maximum likelihood (ML) estimation methods for confirmatory factor analysis, which led to the ML estimation of models that combined confirmatory factor analysis and path analysis (Joreskog, 1970, 1973; Keesling, 1972). ML estimation allowed testing of individual direct effects and error-term correlations, and it is still the most widely used estimation method for SEM.

(E) Model Specification and Identification

An SEM is constructed in terms of postulated direct effects between variables and optional error-term covariance. Each postulated effect corresponds to a parameter, which can be set as free, or constrained to be zero or equal to other parameters. Potential types of parameters include 1) the effect of exogenous variables on endogenous variables 2) the effect of endogenous variables on each other 3) the effect of latent variables on their postulated observed indicators, i.e., factor loadings; 4) variances of the error terms of each endogenous variable and each indicator; 5) covariance between error terms of any endogenous variables and indicators.

Modern SEM software uses matrix notation, symbolic equations or graphical representations in a path diagram to specify an SEM.

Estimation of a model is impossible if more than one combination of parameter values can produce the same covariances. The flexibility of SEM makes it fairly easy to specify an unidentifiable model. There are also cases of empirical under-identification due to special patterns in the data. There are two basic necessary conditions for any type of structural equation model: 1) the number of free parameters can not exceed the number of observations (i.e. the degrees of freedom are greater than or equal to zero). The number of observations equals v*(v+1), where v is the number of observed variables. 2) every latent variable has a scale, which is usually done through a unit loading identification constraint.

Overall the identification of SEM is still an open problem. Only heuristics are available to guide the modeler and the coverage is far from complete. For example, for the measurement sub-model, the “three measure rule” asserts that a measurement model will be identified if every latent variable is associated with at least three indicators; for the structural sub model, all recursive models will be identified as long as there are no error-term correlations. See reviews in Bollen (1989).

For non-recursive models, the identification is more complex. Although there are algebraic means to determine whether the parameters of a non-recursive model can be expressed as unique functions of its observations, these techniques are practical only for very simple models (Berry 1984). There are alternative rules that can be evaluated by hand. One is the necessary order condition which requires that the number of excluded variables for each endogenous variable equals or exceeds the total number of endogenous variables minus 1. The other is the sufficient rank condition which requires that the rank of each of the reduced system matrixes is greater than or equal to the total number of endogenous variables minus 1. Please refer to Berry (1984) for the definition of the system matrix and reduced system matrix.

But in non-recursive model with no disturbance correlations or less than full possible disturbance correlations, the order and rank condition are generally too conservative. Kline (2005) noted that in these cases, there are no easily applied criteria and the identification status of such models may be ambiguous.

(F) Model Estimation

The general SEM system is estimated using covariance (structure) analysis, whereby model parameters are determined by minimizing the difference between the variances and covariances of the variables implied by the model system and the observed variances and covariances of the sample while respecting the constraints of the model.

The mostly commonly used SEM estimation methods today are normal-theory ML, generalized least squares (GLS), and weighted least squares (WLS). ML is the method used most often. The ML solution maximizes the probability that the observed covariances are drawn from a population that has its variance–covariances generated by the process implied by the model, assuming a multivariate normal distribution. ML estimation is fairly robust against violations of multivariate normality for sample sizes commonly encountered in transportation research (Golob 2003; Finch et al., 1997; Kline 2005). Corrections have also been developed to adjust ML estimators to account for non-normality including a robust ML standard error estimator (Browne, 1984).

(G) Assessing goodness-of-fit

Many criteria have been developed for assessing goodness-of-fit of an SEM and measuring how well one model does versus another model (See Bentler 1990, Hu and Bentler 1999 for overviews.)

Most of these criteria are based on the chi-square statistic given by the product of the optimized fitting function and the sample size. The objective is to attain a non-significant model chi-square since the statistic measures the difference between the observed variance-covariance matrix and the one produced by the model.

There are problems associated with the use of the fitting function chi-square mostly due to the influence of sample size. For large samples, it may be very difficult to find a model that cannot be rejected due to the influence of sample size. Many of the goodness-of-fit indices use normalization to cancel out the sample size in the chi-square functions, such as root mean square error of approximation (RMSEA) which measures the discrepancy per degree of freedom (Steiger and Lind 1980). RMSEA is one of the favored statistics because its confidence interval can be calculated as well as the mean value. It is generally accepted that the value of RMSEA for a good model should be less than 0.05 (Browne and Cudeck 1992), but there are strong arguments that the entire 90% confidence interval for RMSEA should be less than 0.5 (MacCallum et al 1996).

There are also goodness-of-fit measures based on the direct comparison of the sample and the model-implied variance-covariance matrices including the standardized root mean square residual (SRMR), which ranges from 0 to 1, with values less than 0.05 being considered a good fit (Byrne 2001; Steiger 1990).

Bentler's comparative fit index (CFI, Bentler 1990) is another often used goodness-of-fit measure. CFI assesses the relative improvement in fit of the researcher's model compared with a baseline independence model, called the null model, which assumes zero population covariances among observed variables. A rule of thumb is that values greater than 0.90 may indicate reasonably good fit of the proposed model. (Hu & Bentler 1999)

Kline (2005) warns about the use of these goodness-of-fit indices:

1) Values of fit indices indicate only the average or overall fit of a model. It is thus possible that some parts of the model may fit the data poorly even if the value of a particular index seems favorable

2) Because a single index reflects only a particular aspect of model fit, model fit should be assessed based on the values of more than one index. There is no single "magic index" that provides a gold standard for all models.

3) Fit indices do not indicate whether the results are meaningful theoretically.

4) Value of fit indices that suggest adequate fit do not indicate that the predictive power of the model is also high.

(H) Applications in transportation:

Most applications of SEM have been in psychology, sociology, the biological sciences, educational research, political science, and market research. Applications in travel behavior research date from 1980.

Golob (2003) offers a summary of the application of SEM in travel behavior research including more than 50 studies up to 2003. These studies range from travel demand modeling using cross-sectional data, dynamic travel demand modeling, activity-based travel demand modeling, applications to capture attitudes, perceptions and hypothetical choices, organizational behavior and values, and driver behavior. Below are a few examples of the applications to capture attitudes, perceptions and hypothetical choices:

Dobson et al 1978 used structural models to examine the attitude-behavior relationship and concluded that attitudes are conditioned by choices while at the same time, attitudes affect choices. The study demonstrates a mutual dependence between attitudes and behavior in the context of behavioral choice situations: behavior and attitudes concurrently cause each other.

Golob and Hensher (1998) employ SEM to examine the relationship between individual's travel behavior and his/her support for policies that are promoted as benefiting the environment.

Morikawa and Sassaki (1998) employ an SEM with a discrete choice model to capture the influence of latent subjective attributes of choice alternatives on choices. Using a Dutch survey of intercity travel and joint ML estimation, the study concludes that models with causality only from attitudes to behavior perform less well than those with

causal links in both directions. The preferred model estimated the SEM and discrete choice model simultaneously.

Jakobsson, Fujii and Garling (2000) use an SEM with five latent variables to investigate causality among acceptance of road pricing, behavioral intention concerning reductions in car usage and feelings related to fairness and infringement on personal freedom. ML is applied using data from a Swedish survey.

Golob (2001) tests a series of joint models of attitude and behavior to explain how both mode choice and attitudes regarding a combined HOV and Toll lanes differ across the population. It is estimated based on a dataset from San Diego, CA. The study demonstrates that choices appear to influence some opinions and perceptions, but other opinions and perceptions are independent of behavior and dependent only on exogenous personal and household characteristics. None of the models found any significant effects of attitudes on choices.

Outwater et al (2003) used an SEM to simultaneously identify traveler attitudes and the causal relationships between traveler's socioeconomic profile and attitudes in evaluating expanded ferry service for the San Francisco Bay Area Water Transit Authority. The study expanded the mode choice model to recognize travelers' attitudes and different market segments. Three attitudinal factors were used to partition the ferry-riding market into eight segments. Mode choice models were then developed for these market segments which recognized that mode choices were different for market segments that were sensitive to travel stress or the desire to help the environment.

Kitamura and Susilo (2005) used SEMs to examine the stability of travel patterns over time based on repeated cross-sectional data from Kyoto-Osaka-Kobe metropolitan area of Japan in 1980, 1990 and 2000. The study found that the changes in the travel pattern are largely due to the instability of the structural relations while changes in demographic and socio-economic factors play relatively minor roles.

More recent applications include:

Ory and Mokhtarian (2009) used SEMs to examine the relationship among travel amounts, perceptions, affections and desires for five categories of short-distance travel based on data collected in 1998 from over 1300 commuters in the San Francisco Bay Area. The robust relationships found across five travel categories include travel amounts influencing perceptions, and both perceptions and affections shaping desires;

Choocharukul, Van and Fujii (2008) examined the psychological effects of travel behavior on preference of residential location choice using SEM. The study found that preference regarding residential location was significantly affected by behavioral intention towards car usage.

2.3.4 Integrated framework

There are efforts to develop an integrated framework from both lines of developments: researchers in discrete choice modeling have introduced latent variables to choice modeling and researchers in structural equation modeling have tried to include categorical dependent variables in their framework.

(A) Sequentially Estimated Models

The simplest way to introduce attitudinal and perceptual variables into mode choice models is to perform sequential estimation as in Vredin Johansson et al (2006). In the first step, a MIMIC model is estimated and factor scores of latent variables are calculated. In the second step, these fitted factor scores are included in the utility function. The two-step limited information estimation method is computationally straightforward but it may result in different estimation problems depending on how the fitted latent factor scores are treated in the second step:

1) If both the fitted latent variables and their distributions are used in the choice model in which the choice probability is integrated over the distribution of the latent variables, the two step estimation method results in consistent but inefficient estimates. (See McFadden 1986)

2) If the fitted scores of latent variables are treated as non-stochastic, the problem is more serious: it introduces measurement error to the utility function and results in inconsistent estimates of the parameters. (Ben-Akiva and Walker et al 2002)

Furthermore in the two-step method latent variables are defined independent of the revealed mode choice, and complex behavioral structure, such as the indirect effects of SES variables on mode choice via latent variables cannot be tested.

(B) Generalized RUM

Walker and Ben-Akiva (2002) developed a generalized RUM model that incorporates four extensions, all of which are estimated simultaneously:

1) Flexible disturbances in order to allow for a rich covariance structure and enabling estimation of unobserved heterogeneity through random parameters;

2) Latent variables in order to provide a richer explanation of behavior by explicitly representing the formation and effects of latent constructs such as attitudes and perceptions;

3) Latent classes in order to capture latent segmentation in terms of, for example, taste parameters, choice sets, and decision protocols;

4) Combining revealed preference data and stated preference data in order to take advantage of the two types of data, thereby reducing bias and improving efficiency of parameter estimates.

The generalized models often result in functional forms composed of complex multidimensional integrals. Simulated Maximum Likelihood Estimation is introduced for practical estimation.

(C) General Latent Variable Modeling

Muthen (2002) is an example of the development of an integrated modeling framework from the SEM tradition. It expanded the models using continuous latent variables to include categorical latent variables. Using traditional structural equation modeling as a starting point, the paper showed how the idea of latent variables captures a wide variety of statistical concepts, including random effects, missing data, sources of variation in hierarchical data, finite mixtures, latent classes, and clusters. These latent variable applications went beyond the traditional psychometrical focus on measurement error and hypothetical constructs measured by multiple indicators. A unifying framework brought together different analysis types as factor models, growth curve models, multilevel models, latent class models and discrete-time survival models in one general model. The SEM software package Mplus is based on this framework.

2.3.5 Latest applications

Since the development of these integrated modeling frameworks, there are several recent applications in transportation and related fields, including:

Johansson et al (2006) modeled five latent variables and three alternative travel modes and examined the effects of attitudes and personality traits on mode choice. Based on a commuter survey in Sweden, the paper found that both attitudes towards flexibility and comfort, as well as being environmentally inclined, influence the individual's choice of mode. Though the paper quotes the integrated choice and latent variable framework (Ben-Akiva et al 1999), the model is estimated in two steps where the latent variables are estimated in a MIMIC model first and then the discrete choice model is estimated, instead of being estimated simultaneously.

Choo and Mokhtarian 2004 explored the relationship between consumers' travel attitudes, personality, lifestyle and subjective mobility, and individuals' vehicle type choices. Sixteen latent variables are identified first using factor analysis and are then included in the MNL model together with ten demographic variables. Based on the 1998

San Francisco Bay Area survey of 1904 results, the authors found that these latent variables significantly affect an individuals' vehicle type choice.

Ashok et al 2002 presented two applications that accommodate latent variables such as attitudes and satisfaction in the context of binary and multinomial choice models. The first application was a binary switching model of cable television providers including latent factors satisfaction (with three indicators) and barriers (with five indicators). Each respondent in the study was asked to make repeated choices so the correlated response model was used to control the within-respondent choice dependency. The second application was in the context of health care providers with two latent variables: satisfaction with cost and satisfaction with coverage. Finite mixture model (latent class) is used to test the heterogeneity in the individuals' choice behavior. Two latent segments are identified with different sensitivities to the satisfaction of cost. Both models are estimated simultaneously by programming maximum likelihood in GAUSS.

Walker and Li 2006 employed a latent class model to simultaneously identify three heterogeneous lifestyle groups: suburban dwellers, urban dwellers and transit-riders, and examine how lifestyle impacts residential location decisions. The model did not include psychometric indicators that provide direct information on attitudes, perceptions and lifestyles.

Temme et al 2008 presents an integrated choice and latent variable model to examine the travel mode choice of a group of 907 German commuters. The latent factors examined included power and hedonism as well as attitudes toward flexibility. Hierarchical relationships between the latent variables (specifically the value-attitude hierarchy) were estimated simultaneously with the mode choice model. The paper also demonstrated that a complex integrated choice and latent variable model can be estimated using the structural equation model package Mplus.

More relevant application oriented literature will be reviewed in each chapter.

2.4 Data

The constraints on data availability to capture the psychological factors are real and serious. In contrast to the socio-economic information for which there are well established institutions such as Census Bureau in the US and the Office for National Statistics (ONS) in the UK responsible for collecting data, the data collection on people's psychological states such as attitude, perception and personality are limited in range of coverage, inconsistent in methodology, and ad hoc in availability. Transportation agencies rely on the social infrastructure for data collection and are therefore constrained by the data availability on these latent factors.

In the 1970s, the date required for disaggregate travel demand analysis was to survey individuals on their travel behavior, through home and telephone interviews, and particularly through travel diaries. Later on board travel survey was developed thanks to choice-based sampling techniques. (Manski and Lerman 1977)

Two major innovations in data collection relevant to this dissertation include conjoint analysis (Stated Preferences) and psychometric data.

2.4.1 Conjoint analysis from market research

Marketing researchers have long used conjoint analysis (stated preference) data to provide insight into consumer preferences. The analysis of stated preference data originated in mathematical psychology by Luce and Tukey (I964). The basic idea is to obtain a rich form of data on behavior by studying the choice process under hypothetical scenarios designed by the researcher. There are many advantages to these data including the ability to: capture responses to products not yet on the market, design explanatory variables such that they are not collinear and have wide variability, control the choice set, easily obtain numerous responses per respondent, and employ various response formats that are more informative than a single choice (for example. ranking, rating, or matching). See Carroll and Green (1995) for a discussion of the methods and Louviere et al. (2000) for a general review of issues.

The primary drawback to stated preference data is that they may not be congruent with actual behavior. For this reason, procedures for combining revealed and stated preference data have been developed in the late 1980's and are being widely applied (Ben-Akiva and Morikawa 1990, Ben-Akiva et al 1994). Exploiting the advantages of both RP and SP data, these methods improve the accuracy of parameter estimation by sharing some of the parameters between the RP and SP models and calibrating location and scale required to adjust for the behavioral response differences between real and hypothetical choice situations.

Conjoint analysis has proven that it can give a much more rounded view of the preferences of an individual than the one-dimensional picture provided by revealed preference data.

2.4.2 Psychometric data

As discussed in section 2.2.6 on latent constructs and their measurement, psychometricians have pioneered the use of psychometric data, such as answers to survey questions regarding attitudes, perceptions, motivation, and intentions.

Some agencies have undertaken customer research that includes elements of psychometric questions to understand travelers' psychological concerns. For example, Transport for London has been the leader in this area by engaging in research such as Central London Congestion Charge Social Impact Surveys 2002 and 2003 (Transport for London 2003), and Londoners' Lifestyle and Car Dependency Survey (Transport for London 2006). The latter is used as the main data source of this dissertation and will be described in Chapter 3.

2.5 Computation and Software

2.5.1 Simulation

As Ben-Akiva, McFadden et al (2002) summarize, a key factor promoting the application of flexible model forms is the advance of simulation techniques. Use of simulation

methods has provided the most traction in obtaining practical representations and estimates for computationally difficult models. The first development of these methods for the multinomial probit model, by Manski & Lerman (1981), was followed by McFadden (1989) which clarified the statistical theory of estimation using simulation methods. This approach to estimation has benefitted from a great deal of research in the last decade on various practical simulators, including the use of Gibbs, Metropolis-Hastings, and other Monte Carlo Markov Chain samplers, use of pseudo-random and patterned random numbers such as Halton and Sobel sequences, and tools such as the simulated EM algorithm and the Method of Simulated Moments; see Bhat (2000), McFadden (1997), and Train (1999). These methods have made it feasible to work with quite flexible models, such as multinomial probit and mixed multinomial logit and extreme value models.

Much recent work has focused on the generation of simulation draws. Bhat (2001) describes the use of Halton draws, a type of quasi-random Monte Carlo method. He found that Halton draws improve the estimation of mixed logit by making it faster and more stable with fewer draws compared to pseudo-Monte Carlo draws.

2.5.2 Software development:

When the complex flexible structure models were first developed, researchers often had to develop customized code for the specific model specification in GAUSS or Matlab. This made it almost impossible for transportation planners to apply these models in practice.

The availability of estimation procedures is critical for the development of hybrid choice models, and even more so for their application in transportation planning. Many advanced discrete choice methods and SEM are available in commercial and free statistical packages.

Researchers are also making their code available. For example, Kenneth Train provides Gauss-based and Matlab-based codes for mixed logit. A new freeware package for the

estimation of GEV models, BIOGEME, was developed by Michel Bierlaire for maximum-likelihood estimation of the GEV model family and has now been extended to mixed GEV models. (Bierlaire 2003)

Use of SEM is now rapidly expanding as user-friendly software becomes available. LISREL, AMOS, and Mplus are three popular statistical packages for doing SEM. LISREL popularized SEM in sociology and other social sciences and is still the package of reference in most articles using structural equation modeling (Joreskog et al 1970). AMOS (Analysis of MOment Structures) is a more recent package which, because of its user-friendly graphical interface, has become popular as an easier way of specifying structural models. AMOS also has a BASIC programming interface as an alternative. (See Kline 2005 for a review of the software packages).

Mplus version 5.1 is one of the most comprehensive software packages for SEM (Muthén and Muthén 2007). In addition to the full flexibility of an SEM program to specify complex structures of latent variables, both numerical and Monte Carlo integration are available for simultaneously estimating a multinomial logit model with latent variables. Mplus allows one to perform both conventional as well as robust maximum likelihood estimation. Although the original SEM assumes continuous latent variable and continuous indicators, Mplus implements the generalized latent variable modeling framework (Muthen 2002) and allows for a proper treatment of various data types (e.g., ordered and unordered categorical) for both observed variables and latent variables. This dissertation uses Mplus' ability to handle nominal indicators to represent the mode choice and car ownership choice. Temme et al (2008) uses Mplus to estimate integrated choice and latent variable models of travel mode choice. Abou Zeid (2009) uses Mplus to estimate an SEM with ordered categorical indicators.

2.6 Summary

This chapter identifies four barriers that have prevented transportation agencies from incorporating psychological factors into transportation planning. The literature review

shows that there have been innovations in behavioral theory, statistical methods, data collection and software packages that have helped to reduce these barriers. In combination these innovations provide transportation planners with the methodological and practical foundation for a systematic treatment of traveler preferences in the planning process.

Chapter 3. A Proposed Structure for Analyzing Traveler Preferences

This chapter proposes a structure for analyzing traveler preferences to organize the factors that influence travel behavior and illustrates the structure using a set of eight latent factors. These eight latent factors are chosen for their behavioral significance and they are supported by the data that are available to this research. These eight latent factors will be used throughout the dissertation to examine impacts on various aspects of travel behavior.

Three EFA models and one CFA model are used to quantify the latent factors based on the psychometric indicators in the survey. A MIMIC model is estimated to examine the interrelationships among these latent factors and between them and travelers' socio-economic characteristics.

Section 3.1 describes the propose structure for analyzing traveler preferences; section 3.2 introduces the data sources and defines the variables; section 3.3 describes the EFA and CFA models for the measurement of the latent factors; section 3.4 specifies the MIMIC model and interprets the two main results: the interrelationships among latent factors, and the relationships between the latent factors and social economic status variables; section 3.5 summarizes the findings of this chapter.

3.1 A Structure for Analyzing Traveler Preferences

Traditional travel behavior models treat traveler preferences as a black box and focus on the direct mapping between alternative attributes and travel behavior. Transportation agency studies of traveler preferences still largely focus on people's responses to travel time and travel cost, and their differentiation across traveler's observed socio-economic characteristics.

However the factors people consider in making their travel decisions are much richer than just travel time and cost, and people's travel preferences are much more complex

than can be differentiated by their socio-economic characteristics. As reviewed in Chapter 2, recent developments including latent variables, latent classes, SEM, and integrated frameworks have advanced ways to examine a wider array of variables that might influence travel behavior and explicitly treat psychological factors such as attitudes and perceptions through psychometric indicators (Ben-Akiva et al. 1994; Morikawa et al, 1996; Gopinath 1995; Walker and Ben-Akiva 2002; Ashok et al 2002; Vredin Johansson, Heldt, and Johansson 2006; Temme et el 2008). These innovations could enable transportation planners to expand the scope of traveler preferences considered in planning.

This section will present a four-group categorization of the factors determining travel behavior, discuss the dichotomy between internal preferences and the external environment, and describe the eight latent factors that are chosen to illustrate the structure for analyzing traveler preferences.

3.1.1 Categorization of the factors influencing travel behavior

There are many factors that may influence travel behavior including those that are already considered in transportation agencies and those that are not. Table 3-1 categorizes them into four groups and comments on their use in planning both in terms of measurability and predictability.

The first group is the classical level of service (LOS) variables describing the attributes of the travel options. They are in general well monitored and usually included in the quantitative tools used in transportation agencies. Their values can be forecast based on future transportation plans such as infrastructure development plans, service change plans, and price adjustment plans.

The second group is travelers' perceptions of the travel options including convenience, comfort, safety, crowding, and cleanliness. Perceptions are rarely systematically measured and never included in forecasting in transportation agencies.

The third group is the observed socio-economic status (SES) variables. They are readily available from household surveys or census and most agencies include them in their planning practice. Their forecast is usually performed by dedicated government agencies such as economic development agencies or by private firms. Transportation agencies usually take them as given in their transportation plans. In the case of London, TfL obtains socioeconomic forecasts from GLA Economics, the economics research unit in the Greater London Authority (GLA).

The fourth group is the attitudes and personality traits of the decision makers. They are rarely monitored and even when they are, they are not integrated into transportation models. They are never included in forecasting.

Table 3-1 Variables Influencing Travel Behavior

Category	Variables	Measurability	Predictability
Level of Service	Travel cost, travel time (riding, waiting, walking), transfers, parking availability, car ownership, …	• Well monitored • Widely used in quantitative models	• Relatively well predicted based on future transportation plan such as infrastructure development, scheduling changes and pricing structure adjustment
Perceptions	Safety, reliability, convenience, level of information, crowding, cleanliness, comfort, visual, pedestrian friendliness, …	• Rarely systematically or consistently monitored • New technologies start to help measurement	• Never used in forecasting
Socio-economic Status	Age, gender, social status, income, employment, household structure,…	•Readily available from household surveys or census	• Transport agencies use socioeconomic forecasts from other municipal or national agencies
Attitudes & Personality	Social image, environmental attitudes, social responsibility, lifestyle, personality, …	•Rarely monitored and never integrated into transportation models	• Never used in forecasting

3.1.2 Dichotomy between internal preference and external environment

Following Simon (1956), this dissertation makes a distinction between transportation system attributes and traveler preferences. From the travelers' point of view, the former is the external environment, the latter is the internal decision criteria and travel behavior is a function of both. This is a customer-centric approach, in which "internal" and "external" are relative to customers as opposed to the commonly accepted stand point which is transportation-agency-centric.

Given this distinction, variables in Category 1 are direct descriptions of the transportation system attributes, which belong to the external environment. Variables in Categories 2 through 4 are internal to the decision makers and are treated as elements of traveler preferences. In this way, this dissertation proposes a structure for analyzing traveler preferences that includes three parts: perceptions, socioeconomic characteristics, and personality and attitudes.

Socioeconomic characteristics are observed elements of traveler preferences and perceptions and personality and attitudes are latent elements of traveler preferences. Socioeconomic variables are only a limited and partial description of traveler preferences. As this chapter will demonstrate, variations among personality traits, attitudes and perceptions do not match well with the socio-economic categorization of the population, and these latent factors are distinct dimensions of traveler preferences.

It has long been debated to what extent the external environment can be distinguished from the internal preferences (Simon 1956). For example, perceptions are subjective reflections of the external system in people's mind and lie at the interface between the external environment and internal preferences. But given the subjective nature of the perceptual constructs, they are treated here as part of the internal preferences.

Making this dichotomy clear could encourage transportation agencies to recognize the importance of both influences and strike a balance between their interests in traveler preferences and in transportation systems. Chapter 7 will discuss recommendations to shift from transportation system centered planning to recognize the role of traveler preferences more explicitly.

As a planning tool, this structure of traveler preferences helps transportation agencies systematize the policy variables already being examined in planning practice and identify holes in the structure that exist in current practice. Transportation planners can position various determining factors within this structure and organize them in a more disciplined manner.

3.1.3 Description of the eight latent factors

To illustrate this structure for analyzing traveler preferences, the remainder of this dissertation uses a set of eight latent factors grouped under categories of personality, attitudes and perceptions, as well as the socio-economic status variables as shown in Figure 3-1. These factors are not intended to be comprehensive and are rather seen as examples of a potentially very large set of factors. For example, convenience and comfort are only two of the many perceptual factors that influence travel behavior with others including safety and cleanliness.

These eight latent factors are chosen for their behavioral significance and they will be used to examine impacts on various aspects of travel behavior. They are supported by the data available for this research: all eight latent factors are measured by at least four indicators in this research, satisfying the identification requirement of the measurement model (Bollen 1989).

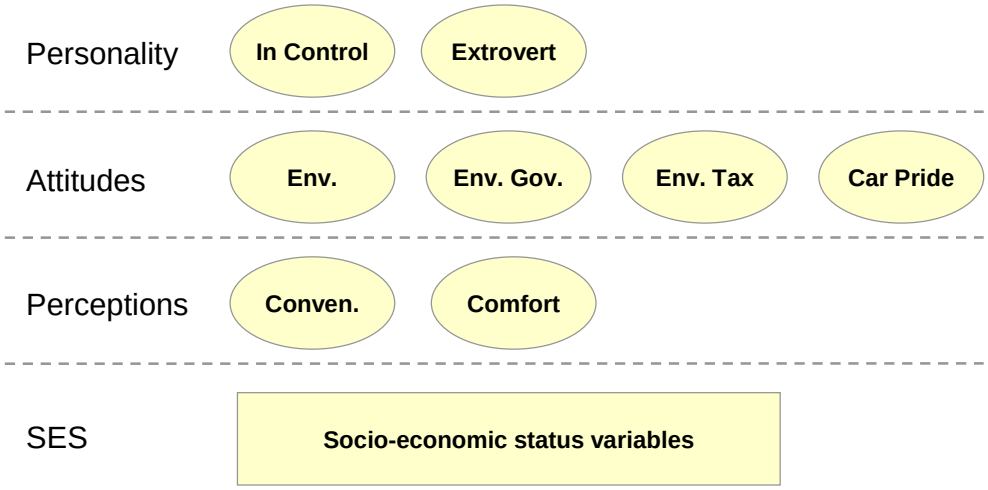


Figure 3-1 Example structure of traveler preferences with eight latent factors

The two personality factors are liking to be “in control” and being “extrovert”. Gardner and Abraham (2006) identified the desire for control as one of the important factors that influence car use, and participants in their survey valued car use for its provision of optimal control. Prevedouros (1992) studied the association between being socially extrovert and travel behavior. Specifically, the study found that socially extrovert people

tend to make more trips, more non-work trips and travel substantially longer distances by automobile for non-work trips compared with socially introverted people.

The four attitudinal factors including three on environmental attitudes: being "environmentally responsible", being "supportive of government actions to protect environment", being "willing to pay more taxes for improving the environment and the public good", and the fourth "car pride".

The environment is becoming a salient factor that enters people's calculus in travel mode choice. In a recent UK Department for Transport evidence review of public attitude towards climate change and transportation behavior, Anable et al (2006) shows a majority of people recognize a link between climate change and transport. UK National Statistic Omnibus Surveys in 2006, 2007 and 2008 reported that around 70% of the population identified transport as a cause of climate change. Nilsson and Kuller (2000) also found significant correlation between environmental concerns and driving distance and number of trips by different modes based on two samples from Sweden. Flamm (2009) studies the effects of environmental knowledge and attitudes on the numbers and types of vehicles owned per household, annual vehicle miles traveled, and fuel consumption. The study found that households with pro-environmental attitudes own fewer and more fuel-efficient vehicles, drive them less, and consequently consume less fuel than do the households of respondents without pro-environmental attitudes.

The status and identity associated with owning and riding a car are recognized as an important source of attraction to the car. From the very early days of motorization, being a car owner was an envied and respected position (Sandqvist 1997) and ever since the car has continued fulfilling the role of powerful status symbol (Garling and Loukopoulos 2008)

The two perceptual factors are "perceiving car to be more convenient than public transportation", and "perceiving the car to be more comfortable than public transportation". The impacts of convenience and comfort on travel behavior are well recognized as shown in Temme (2008) and Morikawa, Ben-Akiva, and McFadden (1996).

The SES group includes the typical sets of variables: gender, age, income, social grade, ethnicity, employment, car and bike ownership, and household structure (i.e. having children or not, single vs. married).

3.2 Data Source and Variable Definitions

In 2005 and 2006, Transport for London (TfL) carried out a web-based survey supplemented by face-to-face interviews with people aged 65 or above (*Londoners' Lifestyle and Car Dependence Survey,* Transport for London 2006). A total of 2,421 completed questionnaires resulted, of which 1700 individuals are included as the study sample after removing those who live outside Greater London and other inconsistent records. The response rate was 60%, considerably higher than typical response rates for online surveys. This was a result of sending out reminder emails after the first email solicitation.

In addition to the typical set of socio-economic variables (10 categories including 12 dummy variables and two continuous variables as shown in Table 3-2), the survey contains 102 psychometric indicators (see Appendix A for the full set of questions), including

- Attitudinal and personality indicators: 80 statements (labeled as A01 to A80) on attitudes, personality and lifestyle. Each statement has five possible response levels: strongly agree, slightly agree, neither agree or disagree, slightly disagree and strongly disagree which are coded as 2, 1, 0, -1 and -2, respectively.

- Perceptual indicators: 22 statements (labeled as QA01 to QA22) on perceptions of each of the main modes: car driver, car passenger, bus, Tube, national rail, walk and cycle. The perceptual indicators only have two response levels: agree or disagree.

Table 3-2 Social Economic Status Variables

ID	Categories	Value	Frequency	Dummy Label
1	AGE	16~24	15%	Young
		25~54	75%	
		55+	10%	Old
2	Gender	Male	45%	Male
		Female	55%	
3	Income	Units: GBP10,000		
4	Social Grade	Coded as 1, 2, 3, 4, 5, 6, 7		
		1-Lowest Grade; 7-Highest Grade		
5	Ethnic	British	69%	British
		Others	31%	
6	Adults	Single	20%	Adult1
		Couple	52%	
		3+	29%	Adult3
7	Having Children	Yes	36%	HavChild
		No	64%	
8	Employment	Working	78%	Working
		Student	8%	Student
		Other	14%	
9	Car Ownership	0	23%	
		1	46%	CarOne
		2+	32%	CarTwo
10	Having Bikes	Yes	61%	HavBike
		No	39%	

Five additional variables are included to reflect land use and public transportation accessibility:

1) Population density (denoted as D_POP)

Population density is calculated at the London ward level in units of persons per square kilometer. Each individual is assigned the average population density of the ward where he/she lives. There are 624 wards in Greater London with an average population of 12,000 per ward.

[Insert the map of population density of London]

2) Land use and activity mixture (denoted as ENTROP)

The mixture of land use and activities at the ward level is approximated by the mix of trips by purpose. Based on the *London Area Travel Survey (LATS) 2001 (Transport for*

London 2003), trips that are destined to each of the 624 wards in Greater London are counted by purpose classified by work, leisure and shopping, education, going home and others. The entropy of the frequencies of the five trip purposes is calculated for each ward and used as a proxy for the land use and activity mix in that ward, using the equation:

$$H(X) = \sum_{i=1}^{n} p(x_i) I(x_i) = -\sum_{i=1}^{n} p(x_i) \log_b p(x_i) \qquad (3\text{-}1)$$

The logarithm base b is set to 5 in order to normalize the entropy value into the range of 0-1: 0 for no mixture at all (single activity type) and 1 for highest mixture (all trip purposes have equal probability).

[Insert the map of population density of London]

3) Home Location: dummy variables are used to indicate home location in Central, Inner or Outer London (denoted as CENTRALL, INNERL and OUTERL)

4) Public Transport Accessibility (denoted as PTAL)

Public Transport Accessibility Level (PTAL) is developed by TfL as a detailed measure of the accessibility to the public transportation network in London including all public transportation modes, taking into account walk access time and service frequency. It does not consider the travel speed, crowding, or network connectivity. This measure is strictly for the supply of public transportation density (Transport for London 2003 ref#). Each individual is assigned the average PTAL score of the ward where he/she lives. Figure 3-2 shows the map of PTAL distribution in Greater London, in which purple and red indicate higher PTAL score and blue indicates lower PTAL score.

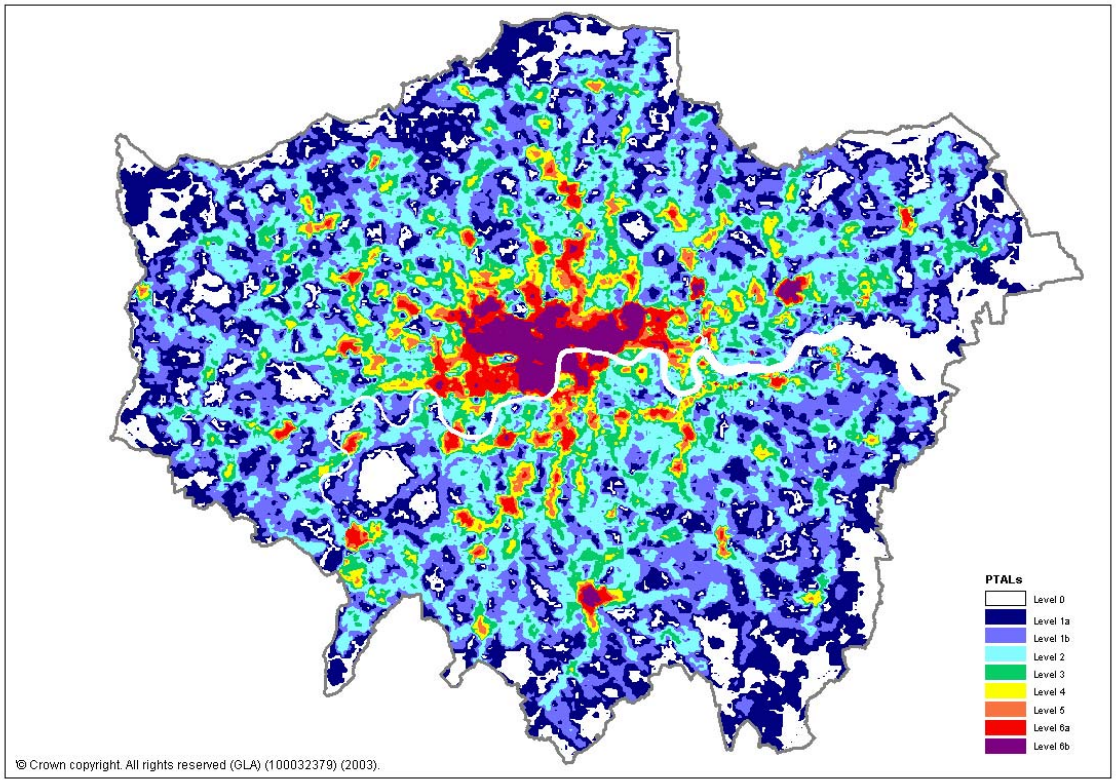


Figure 3-2 PTAL Map of Greater London, Source: Greater London Authority, 2003

5) Access to public transportation stations and stops (denoted as ACCTRAIN)

The *Londoners' Lifestyle and Car Dependence Survey* reports the access distance from home to the closest bus stop, Tube station and National Rail station. The distribution of the access distance by mode is shown in Figure 3-3. Access to bus stop is not used because of its lack of variation with over 90% of the people having access to a bus stop within half a mile of their home. Access to Tube and National Rail is combined to create one dummy variable to indicate if there is any train station available within half a mile of home. This variable is added to supplement the PTAL measure to account for variation within a ward.

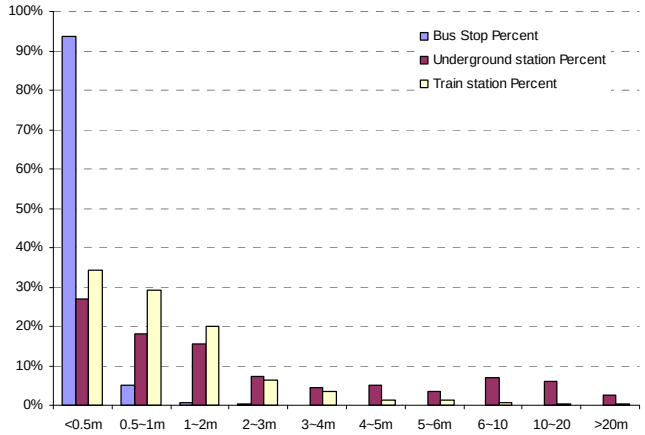


Figure 3-3 Access Distance to Bus Stops, Tube and Rail Stations

3.3 Exploratory and Confirmatory Factor Analysis

As discussed in Chapter 2, there can be a large number of possible combinations in a measurement model with more than just a few variables and exploratory factor analysis (EFA) is sometimes used to guide construction of an SEM measurement model.

In this research 8 latent factors and 39 indicators are involved. Three groups of EFA models are used to identify the relevant indicators for each of the eight latent factors. Within each group, various numbers of factors and indicators are tested and the factor-indicator combination is chosen based on data fit and the interpretability of the constructed factors. Geomin Rotation is used in the EFA, which is an oblique rotation method allowing correlation among the resulting factors but in general facilitating more plausible interpretation of the factors. (See discussion on analytic rotations in Browne 2001.) The EFA models are estimated in Mplus v5.

The first EFA is performed to identify the environmental attitude factors. Seven models were tested with the total number of indicators ranging between 12 and 15 and the number of factors ranging from 2 to 4. After comparing the statistical results and factor interpretability, the 13-indicator, 3-factor model was chosen with the factor loadings shown in Table 3-3. The correlations among the three factors as shown in Table 3-4 are positive as expected. The three factors are called *f_Env*, *f_EnvGov* and *f_EnvTax* based

on the indicators on which each factor has significant loadings. Indicators A10, A12, A13, A14 and A16 are clustered and assess people's general attitude toward the environment by querying their behavior in recycling, water usage etc. Indicators A09, A15, A17 and A18 discuss people's attitude toward the government's role in protecting the environment. Indicators A02, A19, A59 and A66 go one step further and address the willingness to pay taxes in order to protect the environment and the public good in general. Please note the signs of indicators A09, A17 and A18 are reversed so that indicators in one factor group point in the same direction.

Table 3-3 Factor Loadings of the EFA for Attitudinal Factors

Indicators		Factors		
		f_Env	f_EnvGov	f_EnvTax
A10	I recycle most of my rubbish	**0.52**	-0.08	0.00
A12	Environmental concerns were a major factor in choosing the car I have	**0.49**	0.02	0.13
A13	I have looked into dual fuel cars and am interested in getting one the next time I change cars	**0.45**	0.01	0.17
A14	I'm very careful about how much water I use	**0.49**	-0.07	-0.03
A16	Being environmentally responsible is important to me	**0.56**	-0.41	0.00
A09Z	You shouldn't force people to change in order to protect the environment	0.10	**0.64**	0.01
A15	The government should take more of a lead in protecting the environment, even if people don't like it	-0.15	**0.49**	-0.14
A17Z	Environmental threats such as global warming have been exaggerated	0.00	**0.58**	0.01
A18Z	People should be allowed to use their cars as much as they like, even if it causes damage to the environment	0.01	**0.53**	-0.12
A02	I'm happy to pay more tax if the money is spent wisely	-0.01	0.04	**0.65**
A19	For the sake of the environment, car users should pay higher taxes	0.02	-0.18	**0.63**
A59	Charging for road use on a "pay as you go" basis would make people more aware of the real costs of car travel	0.00	-0.14	**0.50**
A66	I would be willing to pay higher taxes on car use if I knew the revenue would be used to support public transport	-0.05	-0.01	**0.84**

Table 3-4 Correlations among Environmental Attitude Factors

Factor Correlations			
Factor	Environ	Env.Gov	Env.Tax
Environ	1		
Env.Gov	0.336	1	
Env.Tax	0.293	0.411	1

The second EFA is for the two latent factors of personality traits: *f_InCtrl* and *f_Extro*. Table 3-5 shows that both factors have six indicators. The correlation between the two factors is 0.003, suggesting that these two factors reflect distinct personality traits.

Table 3-5 Factor Loadings of the EFA for Personality Factors

Indicators	Factors	
	f_InContrl	f_Extrovert
A33 I'm very protective of my personal space	**0.36**	0.09
A34 I always plan things in advance	**0.46**	-0.03
A35 I like to be in control	**0.41**	0.19
A38 I'm always on time	**0.52**	-0.06
A58 If I'm traveling by train to a meeting I'll catch the train before the one I need in case there are delays	**0.45**	0.07
A60 If I'm driving to a meeting I'll allow extra time in case there is congestion	**0.49**	0.00
A39 I often act spontaneously	-0.06	**0.43**
A42 I'm often one of the first people to try out a new product	0.08	**0.46**
A44 I regularly up-date my mobile phone so I have the latest version	0.01	**0.48**
A69 I live a hectic life	0.05	**0.53**
A70 I like to work hard and play hard	-0.01	**0.63**
A71 I go out most evenings	-0.13	**0.55**

The third EFA is carried out for car pride and two perceptual factors: convenience and comfort. Table 3-6 shows the loading for each factor. The indicators for convenience and comfort are asked for each of the six main modes but only have two levels: agree or disagree. The indicators used in the EFA are calculated as the difference between car and the average of bus, Tube and National Rail so that the indicators reflect the relative perceptions of car compared to public transport. Therefore the factors *f_Conven* and *f_Comfort* should be interpreted as perceiving car is more convenient or comfortable than public transport. The signs of the indicators for the factor *f_Comfort* are all reversed since the statements are phrased as opposite to comfort. Table 3-7 indicates positive correlations among these three factors as expected.

Table 3-6 Factor Loadings of the EFA for Car Pride, Convenience and Comfort

Indicators	Factors		
	f_Conven	f_Comfort	f_CarPride
QA1 Ideal for unfamiliar journeys	**0.49**	0.00	-0.04
QA3 Convenient to use	**0.79**	0.01	0.02
QA16 Can get where you want to get to	**0.67**	-0.08	-0.02
QA21 Simple to use	**0.63**	0.07	0.02
QA4Z An unpleasant experience	0.02	**0.64**	-0.03
QA7Z Stressful	-0.12	**0.59**	0.00
QA15Z Are getting worse	0.01	**0.55**	0.01
QA19Z Used by people I am not comfortable with	-0.09	**0.51**	0.00
QA22Z I would be concerned for my personal security	0.01	**0.56**	0.03
A47 Driving gives me a feeling of being in control	-0.01	0.01	**0.70**
A53 I'm proud of my car	-0.01	-0.01	**0.52**
A55 Having a car gives me a great sense of freedom	0.05	-0.01	**0.80**
A62 I like travelling in a car	-0.01	0.05	**0.68**

Table 3-7 Factor Correlations

Factors	Conven	Comfort	Car Pride
Conven	1		
Comfort	0.454	1	
Car Pride	0.283	0.263	1

Table 3-8 summarizes the descriptions of the eight latent factors and the number of indicators for each latent factor which range between 4 and 6.

Table 3-8 Descriptions of Latent Factors and Number of Indicators

Latent Factor	Description	# of Indicators
Personality		
f_InCtrl	liking to be in control	6
f_Extro	being extrovert	6
Attitude		
f_Env	Environmentally responsible	5
f_EnvGov	Supportive of government actions to protect the environme	4
f_EnvTax	Willing to pay more taxes for the environment or the public	4
f_CarPride	Car Pride	4
Perception		
f_Conven	perceiving the car to be more convenient than public transp	4
f_Comfort	perceiving the car to be more comfortable than public trans	5

CFA is then performed to confirm the factor definitions. Table 3-9 shows the loading for all eight factors. The coefficient of the first indicator for each factor is constrained to be 1 as required for identification (the corresponding t-statistic of 999.0 just indicates that it is fixed). The indicators for all eight factors are highly significant.

The overall goodness-of-fit is very good as indicated by the CFI, TLI, RMSEA and SRMR statistics in Table 3-10: CFI and TLI statistics are greater than 0.9 and RMSEA and SRMR statistics are less than 0.05 providing a good indication that the model fits the data well. In particular the entire 90% confidence interval of RMSEA 0.028~0.032 is below 0.05 indicating very good data fit (MacCallum et al 1996).

Table 3-9 Factor Loadings of the Confirmatory Factor Analysis

F_INCTRL	Factor Loading	t
A33 I'm very protective of my personal space	1.000	999.0
A34 I always plan things in advance	0.897	9.5
A35 I like to be in control	1.450	9.7
A38 I'm always on time	1.218	6.9
A58 If I'm traveling by train to a meeting I'll catch the train before the one I need in case there are delays	1.265	7.3
A60 If I'm driving to a meeting I'll allow extra time in case there is congestion	0.819	8.5
F_EXTRO	**Factor Loading**	**t**
A39 I often act spontaneously	1.000	999.0
A42 I'm often one of the first people to try out a new product	0.985	9.7
A44 I regularly up-date my mobile phone so I have the latest version	1.523	10.1
A69 I live a hectic life	1.350	10.0
A70 I like to work hard and play hard	1.839	11.2
A71 I go out most evenings	1.862	11.2
F_ENV	**Factor Loading**	**t**
A10 I recycle most of my rubbish	1.000	999.0
A12 Environmental concerns were a major factor in choosing the car I have	0.866	12.2
A13 have looked into dual fuel cars and am interested in getting one the next time I change cars	0.872	11.7
A14 I'm very careful about how much water I use	0.768	13.8
A16 Being environmentally responsible is important to me	1.279	16.6
F_GOVENV	**Factor Loading**	**t**
A09Z You shouldn't force people to change in order to protect the environment	1.000	999.0
A15 The government should take more of a lead in protecting the environment, even if people don't like it	1.175	14.5
A17Z Environmental threats such as global warming have been exaggerated	1.066	15.5
A18Z People should be allowed to use their cars as much as they like, even if it causes damage to the environment	1.335	14.6
F_TAX	**Factor Loading**	**t**
A02 I'm happy to pay more tax if the money is spent wisely	1.000	999.0
A19 For the sake of the environment, car users should pay higher taxes	1.643	18.3
A59 Charging for road use on a "pay as you go" basis would make people more aware of the real costs of car travel	1.191	16.1
A66 I would be willing to pay higher taxes on car use if I knew the revenue would be used to support public transport	1.399	20.7
F_CarPride	**Factor Loading**	**t**
A47 Driving gives me a feeling of being in control	1.000	999.0
A53 I'm proud of my car	0.832	15.9
A55 Having a car gives me a great sense of freedom	1.082	22.5
A62 I like travelling in a car	0.972	20.9
F_CONVEN	**Factor Loading**	**t**
QA1 Ideal for unfamiliar journeys	1.000	999.0
QA3 Convenient to use	2.030	17.1
QA16 Can get where you want to get to	1.419	15.8
QA21 Simple to use	1.508	16.5
F_COMFOR	**Factor Loading**	**t**
QA4Z An unpleasant experience	1.000	999.0
QA7Z Stressful	1.083	16.1
QA15Z Are getting worse	1.054	16.2
QA19Z Used by people I am not comfortable with	0.644	12.4
QA22Z I would be concerned for my personal security	0.835	15.8

Table 3-10 Goodness-of-fit statistics for CFA model

Overall Model Fit	
Observations	1700
Chi-Square	1554.5
Degree of Freedom	622
CFI	0.927
RMSEA	0.030
90% CI of RMSEA	0.028~0.032
SRMR	0.038

3.4 Multiple Indicators and Multiple Causes (MIMIC) model

3.4.1 Model specification and estimation

In order to examine the interrelationships among the eight latent factors and between them and the socio-economic status variables, a Multiple Indicators and Multiple Causes (MIMIC) model is estimated. Figure 3-4 illustrates the structure of the MIMIC Model and Figure 3-5 specifies the hypothesized relationships among the latent factors. Specifically this model hypothesizes that personality traits influence all other factors; environmental attitudes influence perceptions; and personality traits, environmental attitudes and perceptions of car convenience and comfort all influence car pride.

The MIMIC model simultaneously estimates the measurement equations relating each factor to its indicators; and the structural equations specify the relationships among latent factors and between them and socioeconomic status variables. The estimation of the MIMIC model was conducted in Mplus Version 5 (Muthén and Muthén 2007). Table 3-11 summarizes the overall goodness-of-fit statistics. Though CFI is 0.887 slightly below 0.9, RMSEA and SRMR are below 0.05 and in particular the full 90% confidence interval 0.027~0.030 falls below 0.05 so the overall data fit is acceptable, i.e., the model cannot reject the hypothesis of the relationships among the latent factors and between them and SES variables specified in Figures 3-4 and 3-5.

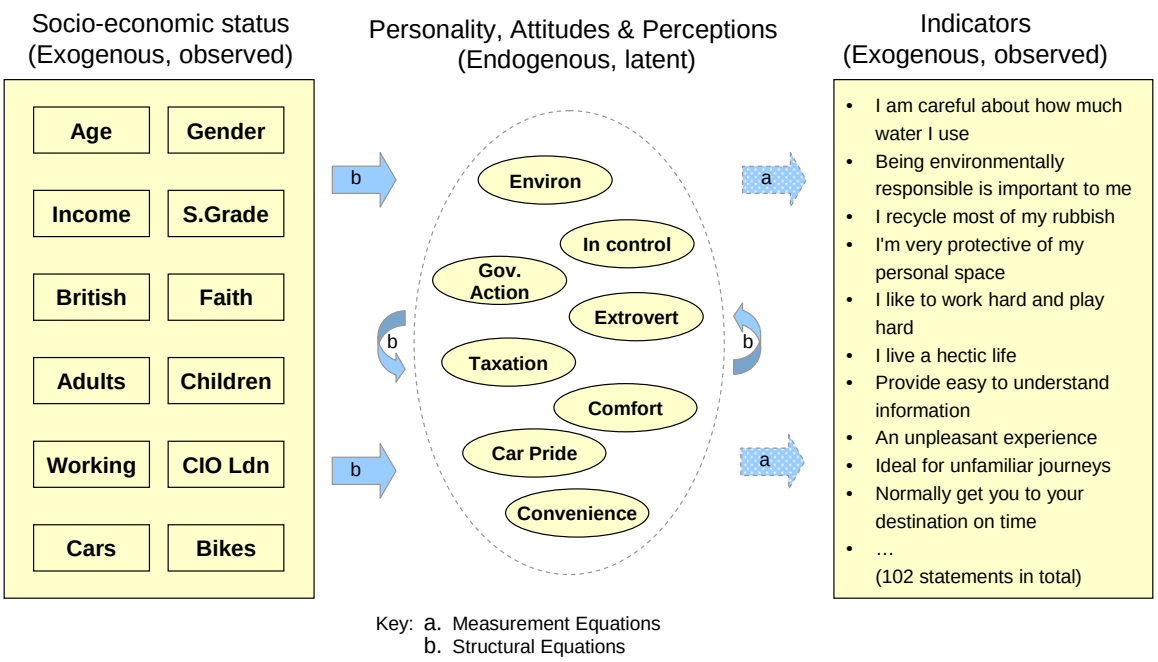


Figure 3-4 Multiple Indicators and Multiple Causes Model (MIMIC)

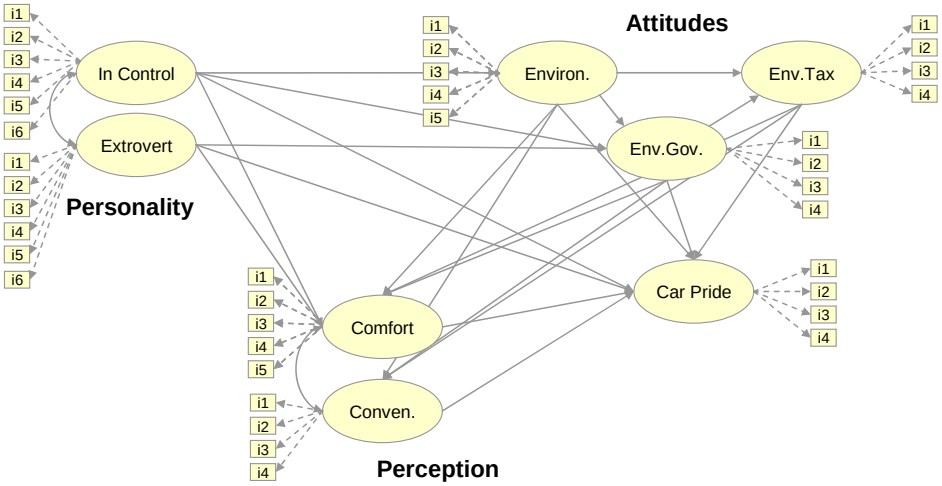


Figure 3-5 Detailed Path Analysis Diagram

Table 3-11 Goodness-of-fit statistics for MIMIC Model

Overall Model Fit	
Observations	1700
Chi-Square	2805.1
Degree of Freedom	1192
CFI	0.887
RMSEA	0.028
90% CI of RMSEA	0.027~0.030
SRMR	0.033

In addition to the overall model fit, two important results of the MIMIC models are the relationships between the SES variables and the latent factors discussed in section 3.4.2, and the interrelationships among the latent factors discussed in section 3.4.3.

3.4.2 Relationships between the SES variables and the latent factors

The relationships between the SES variables and the latent factors are summarized as the regression coefficients shown in Tables 3-12, 3-13 and 3-14: the impacts of SES variables on personality, attitudes and perceptions respectively.

Table 3-12 the Impacts of SES Variables on Personality Traits

SES	F_INCTRL	t	F_EXTRO	t
YOUNG	**0.089**	**2.2**	**0.165**	**4.2**
OLD	0.042	1.0	**-0.228**	**-5.4**
MALE	**-0.082**	**-3.3**	0.033	1.5
BRITISH	**-0.066**	**-2.7**	-0.028	-1.2
SGRADE	0.014	1.5	0.009	1.0
INCX	0.010	1.3	**0.032**	**4.1**
WORKING	0.035	1.0	**0.071**	**2.0**
STUDENT	-0.037	-0.7	**0.105**	**1.9**
ADULT1	0.032	1.0	0.021	0.7
ADULT3	**-0.076**	**-2.6**	**0.081**	**2.9**
HAVCHILD	0.011	0.4	**-0.074**	**-3.0**
CARONE	-0.036	-1.2	-0.017	-0.6
CARTWO	0.016	0.4	0.021	0.6
HAVBIKE	0.000	0.0	0.027	1.2
D_POP	**-0.081**	**-2.0**	0.042	1.1
ENTROP	-0.114	-0.7	0.010	0.1
PTAL	-0.008	-0.7	-0.001	-0.1
OUTERL	0.006	0.2	**-0.079**	**-2.6**

Being young, female and non-British are significantly associated with liking to be in control. Age has a significant negative impact on being extrovert; people with higher income, working or being a student are more extrovert than others, whereas people having children are less extrovert. People who live in Outer London tend to be less extrovert. Car ownership and bike ownership are not significantly associated with people's personality traits. Higher population density is negatively associated with liking to be in control but its underlying reason requires further research.

Table 3-13 the Impacts of SES Variables on Attitudes

SES	F_ENV	t	F_EnvGov	t	F_EnvTax	t	F_CarPride	t
YOUNG	**-0.291**	**-4.7**	**-0.141**	**-2.5**	-0.057	-0.9	0.087	1.3
OLD	**0.131**	**2.1**	0.041	0.7	0.073	1.2	-0.046	-0.7
MALE	**-0.102**	**-3.0**	**-0.131**	**-3.9**	**0.098**	**2.8**	-0.063	-1.7
BRITISH	**-0.136**	**-3.7**	-0.056	-1.6	0.060	1.6	-0.037	-0.9
SGRADE	**0.048**	**3.3**	**0.030**	**2.2**	**0.041**	**2.8**	0.002	0.1
INCX	0.001	0.1	0.011	1.0	**0.030**	**2.4**	0.015	1.1
WORKING	**-0.143**	**-2.6**	0.031	0.6	-0.043	-0.8	0.000	0.0
STUDENT	-0.135	-1.6	-0.001	0.0	0.063	0.7	0.021	0.2
ADULT1	**-0.122**	**-2.7**	-0.040	-0.9	-0.069	-1.5	0.097	1.9
ADULT3	0.049	1.1	-0.006	-0.2	0.043	1.0	-0.001	0.0
HAVCHILD	-0.008	-0.2	**-0.120**	**-3.4**	**-0.112**	**-2.9**	-0.064	-1.6
CARONE	**-0.145**	**-3.3**	**-0.193**	**-4.6**	**-0.405**	**-8.5**	**0.373**	**7.0**
CARTWO	**-0.225**	**-4.2**	**-0.343**	**-6.5**	**-0.570**	**-9.6**	**0.549**	**8.6**
HAVBIKE	**0.196**	**5.5**	**0.137**	**4.1**	**0.197**	**5.5**	-0.060	-1.6
D_POP	0.056	0.9	**0.146**	**2.5**	0.048	0.8	-0.016	-0.2
ENTROP	0.022	0.1	0.152	0.7	0.126	0.5	0.185	0.7
PTAL	-0.006	-0.3	-0.016	-1.0	0.017	0.9	**-0.046**	**-2.1**
OUTERL	-0.045	-1.0	-0.009	-0.2	-0.077	-1.6	0.013	0.2

Car ownership is consistently the strongest negative predictor of environmental attitudes, across all three factors *f_Env*, *f_EnvGov* and *f_EnvTax*; and having two or more cars manifests even stronger negative environmental attitudes than having one car. In contrast, owning a bike is significantly correlated with positive environmental attitudes, across all three factors.

High social grade is associated with positive environmental attitudes *f_Env* and *f_EnvGov*, but income is not, even though social grade and income are positively correlated.

Being old increases the general environmental attitude *f_Env* but not the attitude towards government action *f_EnvGov* or taxation *f_EnvTax* to protect the environment. Being young reduces the general environmental attitude *f_Env* and support for government action *f_EnvGov*. Males have a more negative environmental attitude (*f_Env*) than females, and are less supportive of government action (*f_EnvGov*), but are more willing to pay tax to protect the environment (*f_EnvTax*). Working or being single reduces the general environmental attitude *f_Env*.

Being British negatively influences environmental attitudes but does not significantly impact attitudes towards government action or taxation to protect the environment. Having children does not impact the general environmental attitude *f_Env* but negatively impact the *f_EnvGov* and *f_EnvTax* factors.

Car pride is independent of most of the socio-economic variables including age, gender, income, social grade, employment and household structure, but owning cars is strongly associated with higher car pride. In contrast, better public transportation accessibility is negatively associated with car pride.

Table 3-14 the Impacts of SES Variables on Convenience and Comfort

SES	F_CONVEN	t	F_COMFORT	t
YOUNG	0.023	0.5	**0.102**	**1.9**
OLD	-0.089	-1.8	**-0.248**	**-4.4**
MALE	**0.050**	**1.9**	**-0.089**	**-2.9**
BRITISH	-0.021	-0.7	-0.041	-1.3
SGRADE	-0.019	-1.7	-0.001	-0.1
INCX	0.002	0.2	-0.003	-0.3
WORKING	-0.021	-0.5	-0.048	-1.0
STUDENT	-0.078	-1.2	**-0.220**	**-2.9**
ADULT1	0.055	1.5	-0.008	-0.2
ADULT3	**-0.074**	**-2.2**	-0.046	-1.2
HAVCHILD	**0.064**	**2.2**	-0.037	-1.1
CARONE	**0.394**	**10.0**	**0.129**	**3.2**
CARTWO	**0.591**	**11.6**	**0.217**	**4.5**
HAVBIKE	-0.037	-1.4	0.010	0.3
D_POP	0.021	0.4	-0.062	-1.1
ENTROP	0.142	0.7	0.014	0.1
PTAL	-0.014	-1.0	-0.023	-1.4
OUTERL	**0.085**	**2.3**	0.024	0.6

Owning car(s) increases the positive perceptions of the car's convenience and comfort relative to public transport. Being male, having children or living in Outer London increases the perception of the car's convenience. Age negatively impacts the *f_Comfort* factor. Females perceive the car as more comfortable relative to public transport than do males.

3.4.3 Interrelationships among the latent factors

The significant interrelationships among the latent factors are summarized in Figure 3-6, which shows the standardized coefficients (t-statistics in parenthesis) between latent factors in the path diagram.

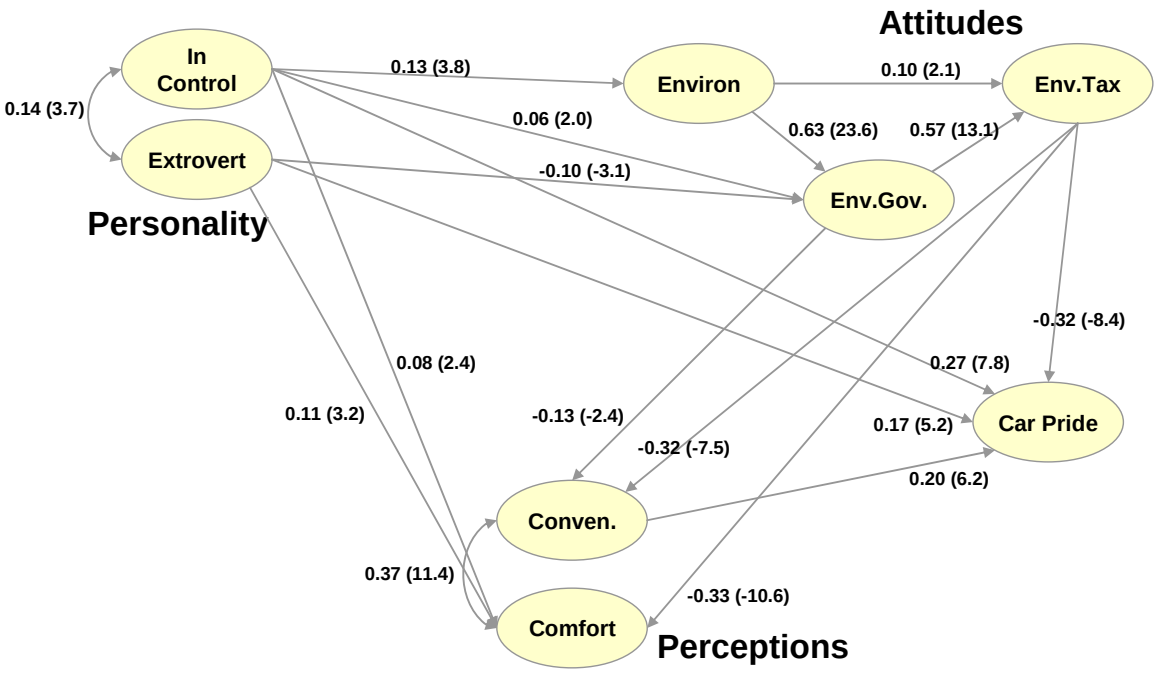


Figure 3-6 Standardized Coefficients between the Latent Factors in the PA Diagram

The relationships among the *f_Env*, *f_EnvGov* and *f_EnvTax* factors, suggest that a pro-environmental attitude leads to more support for government actions to protect the environment, and more willingness to pay taxes to support these government actions. The standardized coefficients of both connections are about 60%--very strong though not exclusive. There are other important factors influencing people's support for government actions or willingness to pay taxes beyond their general environmental attitudes. For example, the level of trust in the government could be another factor. In the 1993 and 1996 British Social Attitudes Surveys, only 37% population reported "some trust" or "a lot of trust" in the government to make the right decisions about the environment, whereas 55% reported "very little trust" or "no trust at all". (UK National Centre for Social Research, 1993 and 1996)

Both personality factors are positively associated with the perception of car comfort, while all three environmental factors are negatively associated with perceptions of car convenience and comfort. Car pride is positively influenced by the personality traits and perception of convenience; and negatively influenced by the *f_EnvTax factor*.

3.4.4 Overall connection between latent factors and SES variables

Despite the significant correlations between SES variables and latent factors, the overall capacity of the SES variables to explain the variation of the latent factors is limited. Table 3-15 reports the R-square of the regressions of latent factors on the SES and land use variables, which range between 5% and 21%, i.e., only 5% to 21% of the variation of the latent factors can be explained by the variation of the SES variables. Liking to be in control is the factor least explained by the SES variables, whereas perception of convenience is the factor most explained by the SES variables. Personality, attitudes and perceptions are characteristics of individuals distinct from the SES variables for which separate measures are needed.

Table 3-15 R-squares of the Regressions of the Latent Factors on the SES Variables

	R2	Beta	t
F_INCTRL		5%	3.6
F_EXTRO		18%	7.7
F_ENV		12%	6.6
F_EnvGov		14%	6.9
F_EnvTax		18%	9.0
F_CONVEN		21%	10.2
F_COMFOR		7%	4.6
F_CarPride		11%	6.0

3.5 Summary

To summarize, this chapter proposed a structure for analyzing traveler preferences including travelers' personality traits, attitudes, perceptions and socioeconomic characteristics, illustrated the structure with a set of eight latent factors. This chapter quantified these eight factors and linked them to the socioeconomic variables using EFA, CFA and MIMIC models. Important relationship between SES variables and latent variables are identified but the overall capacity of SES variables to explain the latent

factors are limited which indicates that these latent factors are distinct elements of traveler preferences that need to be measured separately from the SES variables.

The following three chapters will incorporate these latent factors into transportation models to examine three aspects of travel behavior and demonstrate how such an analysis structure can be useful in understanding travel behavior and improving planning practice.

Chapter 4. Traveler Preferences and Car Use

4.1 Introduction

The number of private cars and car trips has increased dramatically since the 1950s throughout the developed world and more recently also in the developing world, producing both positive and negative effects on cities. The negative external effects of driving, including environmental impacts, energy, safety and livability, argue for restricting car use (Priemus 1995). Transportation policies are often proposed to reduce personal car use in favor of more environmentally friendly alternatives. It is essential for transportation agencies to understand the factors determining car use if effective policies are to be developed to reduce it. Car use and car ownership are intertwined with each other. This chapter focuses on the car usage given the level of car ownership. Chapter 6 will turn the focus to car ownership.

Typical planning models to explain car use include such factors as car ownership, household structure (having children or not, being single or married), income and working status, land use patterns, and public transportation access. This chapter examines the impact of people's personality traits, environmental attitudes and sense of car pride on their car usage, controlling for individuals' socio-economic status, land use, public transportation access and car ownership. The analysis considers both the absolute amount (car trip frequency) and the relative level (car mode share) of individuals' car use, and finds important differences between these two aspects of car use in terms of how they are influenced by people's personality traits, environmental attitudes and car pride.

Traveler preferences (both demographic and psychological factors) and travel behavior have been shown to be statistically significantly correlated (Recker and Golob 1976). But the correlation by itself leaves open the nature of the interrelationship between preferences and behavior. For example attitudes could either cause or be caused by behavior. In fact causalities in both directions can exist concurrently. This chapter

specifies a series of SEMs that hypothesize different causal mechanisms including one-way influence from preferences to behavior and two-way relationships with feedback from behavior to preferences. The potential mutual dependencies between behavior and preferences are tested by comparing these different SEM specifications.

The SEMs also distinguish the direct effects of the SES variables on car use from their indirect effects via the latent factors. Models with and without latent variables are compared to examine whether the impacts of SES variables on car usage will change because of the indirect effects via latent factors.

Section 4.2 reviews the literature on the mutual dependencies between traveler preferences and behavior; Section 4.3 describes the system of models and particularly the specifications of models with and without feedback from behavior to preferences; section 4.4 reports the results of the regression model without latent variables and compares the results based on the full sample and car-owner only sample; sections 4.5, 4.6 and 4.7 reports the result of car mode share models with environmental attitude factors, personality factors, and car pride and perceptual factors, respectively. Section 4.8 compares the car mode share model with car trip frequency models and discusses the different roles of the latent variables in these two aspects of car use; section 4.9 discusses the direct and indirect effects identified by the models with latent factors and compares them with the models without latent factors; and section 4.10 concludes.

4.2 Mutual Dependencies between Preferences and Behavior

Many travel behavior researchers have assumed a one-way causal relationship in which attitudes are determinants of behavior. Morikawa, Ben-Akiva and McFadden (1996) incorporate latent constructs of convenience and comfort in a mode choice model and implicitly assumed that only convenience and comfort influence mode choice but not the other way around. This one-way causation could be misleading if the feedback loop of the mutual dependence exists.

Tardiff (1976) estimated models in which attitudes and behavior are jointly dependent on a third set of variables, i.e., personal and situational descriptors. He found the effect of attitudes on behavior to be substantially weaker than that of behavior on attitudes. Horowitz (1978) employed the cognitive dissonance theory to explain the effect of behavior on attitudes by arguing that attitudes are adjusted by people so that attitudes are consistent with mode choice thereby reducing the cognitive dissonance.

Golob (2001) developed joint models of attitudes and behavior to explain how mode choice and attitude regarding the San Diego I-15 Congestion Pricing Project differ across the population. He found that some aspects of attitudes and perceptions are caused by behavior while others are independent of behavior. The study did not find significant effects of attitudes on mode choice.

Morikawa and Sasaki (1998) proposed a framework composed of a linear structural equation model and a discrete choice model. The two perceptual factors comfort and convenience were found to have outstanding explanatory power in the mode choice model. The authors recognized that respondents may overstate the ratings of their chosen alternative to justify their actual choices to correct the cognitive dissonance. A separate model included a mode choice dummy in the latent factors' measurement equations to adjust for the potential bias in the rating data. The study found that models with causality only from perceptions to behavior performed less well than those that incorporated causal feedback from behavior to perceptions.

Evidence supporting both directions of causality has been found. The more general case is that both causal directions may be operating concurrently (Dobson et al 1978).

4.3 SEM Specifications with and without Feedback Loop

This chapter employs a series of structural equation models that integrate the latent variable model and the car mode share model to analyze the interrelationship between attitudes and behavior. The models are based on a cross-sectional dataset from the Londoner's Lifestyle and Car Dependence Survey introduced in Chapter 3.

One important advantage of SEM is its capacity to test different hypotheses of the causal relationship between variables. Two possible causal relationships between latent traveler preferences and car mode share are tested:

Specification 1: The first assumes influence in one direction from traveler preferences (personality, attitude, car pride and perceptions) to car mode share;

Specification 2: The second assumes a two-way relationship: on one hand, traveler preferences may influence car mode share; and on the other hand, car mode share may influence traveler preferences. The feedback relationships are tested for statistical significance.

The SEM allows the specification of the models with a feedback loop in order to test the two way causal relationship. Figure 4-1 shows the path diagram of specification 1. The diagram shows a typical latent variable model without a feedback loop. All causal relationships are one directional. Specifically, the measurement equations (dotted arrow) specify how latent factors are measured by indicators; the structural equations (solid arrow) specify that the SES variables influence the latent factors, and the latent factors and SES, land use and PT access variables influence car mode share.

Figure 4-2 shows the path diagram with a feedback loop from car share to latent factors to reflect the behavioral hypothesis that attitudes could either cause or be caused by behavior (Golob et al 1978). The models with feedback loops are called non-recursive models in the SEM literature (Kline 2005).

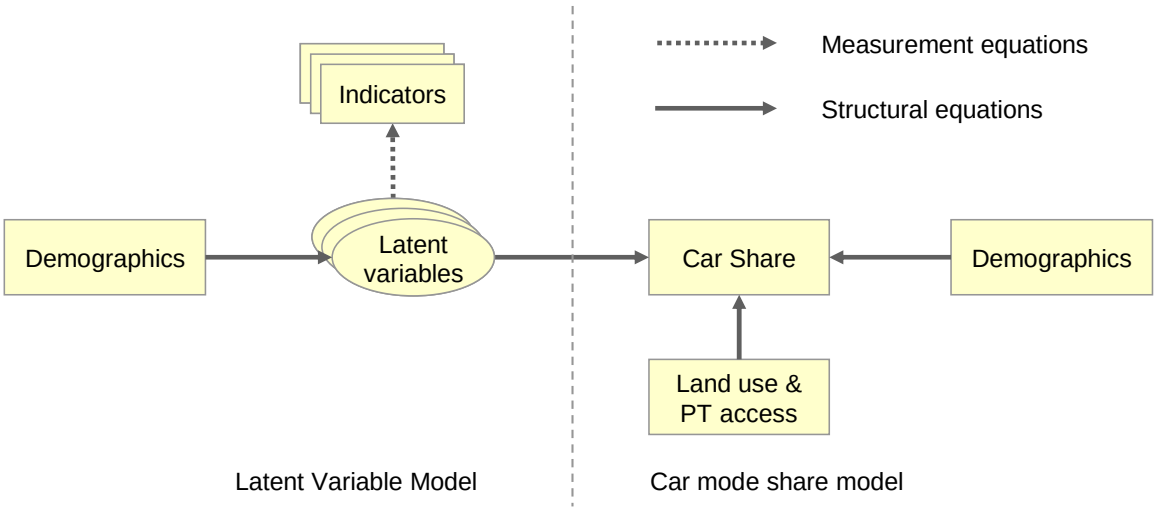


Figure 4-1 Path Diagram for the SEM model without Feedback Loop

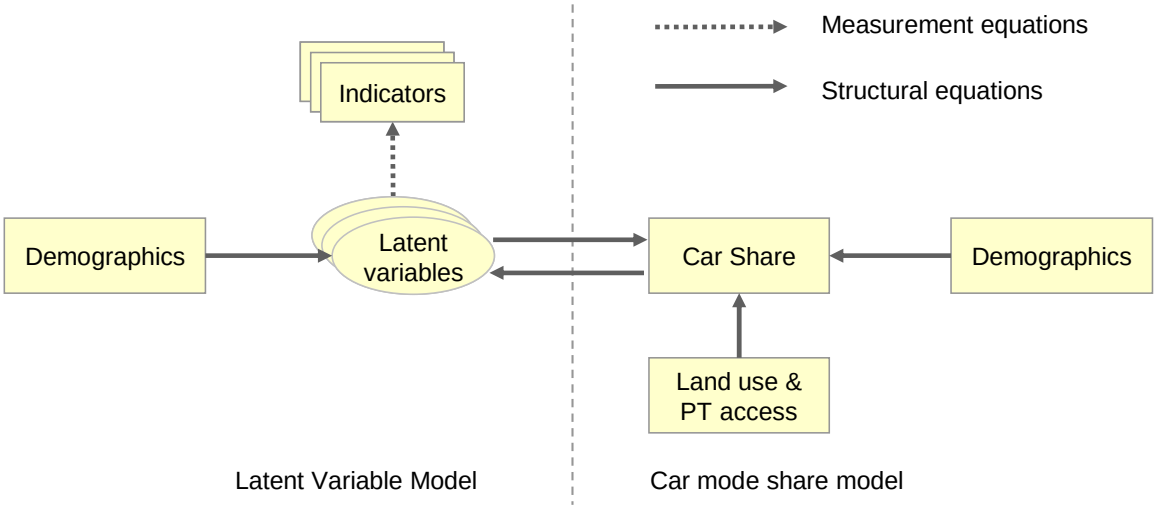


Figure 4-2 Path Diagram for the SEM model with Feedback Loop

The SEM specification allows the use of cross-sectional data to examine the mutual dependencies between behavior and preferences. But as Kaplan et al (2001) has warned data from a cross-sectional design give only a “snapshot” of an ongoing dynamic process. The estimation of mutual dependence with cross-sectional data requires the assumption of equilibrium, i.e., any changes in the system underlying a presumed feedback relation have already manifested their effects and the system is in a steady state. This assumption may not hold for London in 2006 when the cross-sectional data

was collected. Therefore the model results and interpretations reported in this chapter have to be viewed with caution because of this equilibrium assumption.

All together 32 model specifications were estimated, combining the following four dimensions of model variation: dependent variables, independent variable groups including the latent variable groups, with or without feedback from behavior to preferences, and full vs. car owner samples (see Table 4-1).

Table 4-1 Model Variations

Dimensions	# of cases	Cases
Dependent variables	2	Car mode share Car use frequency
Independent variable groups	4	Models without latent factors Models with environmental attitudinal factors Models with personality factors Models with car pride and perceptual factors
Feedback from Behavior to Preference	2	Without feedback (one-way causality) With feedback (two-way causality)
Samples	2	All individuals Individuals owning at least one car

The dependent variables are car use frequency and car mode share. Trip frequency in units of number of trips per day is asked in the *Londoners' Lifestyle and Car Dependency Survey* for each respondent for each main mode. Car mode share is calculated as the ratio of the car trip frequency to the total trip frequency.

The independent variables include three groups:

1) Socioeconomic and demographic variables: 11 categories and 17 dummy variables, as defined in Chapter 3 (see Table 3-2).

2) Land use and public transport access variables: population density, land use mix, public transportation accessibility, and home location in Central, Inner or Outer London, also following the definition in Chapter 3 (see Section 3.3).

3) Latent factors: environmental attitudes, personality traits, car pride and perceptions of convenience and comfort

Models based on only group 1 and 2 variables are estimated as the base models and models with all three groups of variables are implemented as SEMs.

Three sets of SEMs are developed: one for each latent factors group: environmental attitudes, personality traits, car pride and perceptions of convenience and comfort. In each set of the SEMs, model specifications with and without feedback are estimated and compared.

Out of the total sample of 1700 individuals, 1287 individuals own at least one car. Separate models are estimated for both the full 1700 sample and the 1287 car owner sample. All models are estimated in Mplus v5.

4.4 Regression Models without Latent Factors

As the base case, linear regression models are estimated for car mode share and car use frequency with SES variables, land use patterns, and public transportation access as the independent variables. Ordinary linear regression is chosen for its simplicity since the main goal here is to examine how to incorporate latent variables into the model. More advanced model forms will be demonstrated in later chapters.

The left side of Table 4-2 shows the regression results for the car mode share model based on the full sample. Obviously vehicle ownership has the strongest impact on car mode share: on average, owning one car increases car mode share by 23 percentage points and owning two or more cars by 33 percentage points. In contrast, owning a bike reduces car mode share by 4 percentage points.

Having children is the second most important factor, which increases car mode share by 8 percentage points. Being single increases car share while having three or more adults in the household reduces car share.

High population density and better public transportation access both have negative impact on car mode share though their impacts are only marginally significant.

One unexpected result is the significantly negative influence of income. There are two possible reasons for this: the result is after controlling for car ownership so much of the income effect may have been absorbed by car ownership; in London the out-of-pocket cost of public transportation, particularly the Tube, is higher than the cost of using a car[3]. This out-of-pocket cost of using a car does not include the cost of parking in London. Further research is required to get a fuller understanding of this.

Table 4-2 Car mode share and trip frequency models with full sample

Dep. Var.	Car Mode Share		Car Trip Frequency	
Sample size	**1700**		**1700**	
R-Square	**0.295**		**0.286**	
Indep Var	**Estimate**	**t**	**Estimate**	**t**
YOUNG	-0.030	-1.6	0.024	0.7
OLD	-0.002	-0.1	-0.014	-0.4
MALE	-0.005	-0.4	**-0.035**	**-1.8**
CHRIST	0.001	0.1	0.016	0.8
BRITISH	0.007	0.6	0.024	1.1
SGRADE	-0.007	-1.4	-0.002	-0.2
INCX	**-0.012**	**-3.1**	-0.007	-1.0
WORKING	0.003	0.2	-0.004	-0.1
STUDENT	**-0.066**	**-2.4**	**-0.098**	**-2.0**
ADULT1	**0.033**	**2.3**	**0.071**	**2.7**
ADULT3	**-0.033**	**-2.4**	-0.010	-0.4
HAVCHILD	**0.079**	**6.6**	**0.139**	**6.5**
CARONE	**0.227**	**16.1**	**0.442**	**17.7**
CARTWO	**0.328**	**19.2**	**0.575**	**18.9**
HAVBIKE	**-0.038**	**-3.4**	**-0.042**	**-2.1**
D_POP	**-0.036**	**-1.8**	-0.001	0.0
ENTROP	0.031	0.4	-0.159	-1.1
PTAL	-0.010	-1.6	**-0.020**	**-2.0**
OUTERL	0.022	1.5	0.022	0.8

[3] Out-of-pocket costs by mode in London: car 11 pence per km, calculated based on the AA guide to the cost of running a car; Tube, 18 pence per km and Bus, 13 pence per km, calculated as TfL total ticketing revenue divided by the passenger km operated by mode.

The right side of Table 4-2 shows the results for the car use frequency model. Comparing the models for car mode share and car trip frequency shows that the impacts of car ownership, having children, bike ownership, being students and being single are broadly similar. However two differences stand out: first, population density is no longer significant: while higher density decreases the car share it does not influence the absolute level of car trip frequency; second, while income decreases car mode share, it does not significantly influence car trip frequency.

Since most non-car-owners do not use car much, their car mode shares are zero or close to zero. Non-car-owners do not necessarily have a zero car mode share because they can still travel on borrowed or rented cars, or travel as passengers in cars owned by others. By including the non-car-owners in the sample, the model inflates the R-square. Therefore models based on car owner sample are estimated and compared to the models based on the full sample in Tables 4-3 and 4-4.

There are no directional changes in the results based on the two samples. Car ownership becomes much less significant because it only reflects the difference between owning one and two (or more) cars (therefore only one dummy variable is included), instead of between owning a car or not, which is a much more critical difference. The magnitudes of the coefficients of other variables increase by 25%~40% in the car owner sample, reflecting their increased importance with car ownership playing a less dominant role. The R-square is sharply reduced from 0.295 to 0.135 as expected, however it is a more meaningful indicator since it is not inflated by the zero car mode shares of the non-car-owners.

Table 4-3 Car mode share models for the full and car owner samples

	Dep. Var: Car Mode Share			
	Full Sample		Car Owner Sample	
Sample Size	1700		1287	
R-Square	0.295		0.135	
Indep Var	Estimate	t	Estimate	t
YOUNG	-0.030	-1.6	-0.032	-1.3
OLD	-0.002	-0.1	0.003	0.1
MALE	-0.005	-0.4	-0.009	-0.6
CHRIST	0.001	0.1	-0.002	-0.2
BRITISH	0.007	0.6	0.015	0.9
SGRADE	-0.007	-1.4	-0.008	-1.4
INCX	**-0.012**	**-3.1**	**-0.015**	**-3.2**
WORKING	0.003	0.2	0.000	0.0
STUDENT	**-0.066**	**-2.4**	**-0.086**	**-2.4**
ADULT1	**0.033**	**2.3**	**0.052**	**2.6**
ADULT3	**-0.033**	**-2.4**	**-0.044**	**-2.5**
HAVCHILD	**0.079**	**6.6**	**0.097**	**6.6**
CARONE	**0.227**	**16.1**	n.a.	
CARTWO	**0.328**	**19.2**	**0.105**	**6.8**
HAVBIKE	**-0.038**	**-3.4**	**-0.051**	**-3.7**
D_POP	**-0.036**	**-1.8**	**-0.057**	**-2.1**
ENTROP	0.031	0.4	0.013	0.1
PTAL	-0.010	-1.6	-0.013	-1.6
OUTERL	0.022	1.5	0.030	1.5

The comparison of the full sample and the car owner sample for the car trip frequency models produce similar findings as the car mode share models: car ownership plays a less significant role, the relative importance of other variables increases, and the R-square decreases from 0.286 to 0.078.

The overall explanatory power of the models based on car owner sample is low. This may be because some important factors are not included in the models such as road congestion, parking availability etc.

The models based on the car owner sample will be used as the baseline for comparison with the models with latent factors.

Table 4-4 Car use frequency models for the full and car owner samples

Dep. Var: Car Use Frequency				
Full Sample			**Car Owner Sample**	
Sample Size	**1700**		**1287**	
R-Square	**0.286**		**0.078**	
Indep Var	**Estimate**	**t**	**Estimate**	**t**
YOUNG	0.024	0.7	0.033	0.7
OLD	-0.014	-0.4	-0.006	-0.1
MALE	**-0.035**	**-1.8**	**-0.047**	**-1.9**
CHRIST	0.016	0.8	0.018	0.7
BRITISH	0.024	1.1	0.036	1.3
SGRADE	-0.002	-0.2	-0.001	-0.1
INCX	-0.007	-1.0	-0.008	-1.0
WORKING	-0.004	-0.1	-0.002	-0.1
STUDENT	**-0.098**	**-2.0**	**-0.121**	**-1.9**
ADULT1	**0.071**	**2.7**	**0.095**	**2.6**
ADULT3	-0.010	-0.4	-0.009	-0.3
HAVCHILD	**0.139**	**6.5**	**0.167**	**6.3**
CARONE	**0.442**	**17.7**	n.a.	
CARTWO	**0.575**	**18.9**	**0.133**	**4.8**
HAVBIKE	**-0.042**	**-2.1**	**-0.057**	**-2.3**
D_POP	-0.001	0.0	0.006	0.1
ENTROP	-0.159	-1.1	-0.247	-1.3
PTAL	**-0.020**	**-2.0**	**-0.027**	**-1.8**
OUTERL	0.022	0.8	0.036	1.0

4.5 Car Mode share and Environmental Attitudes

4.5.1 Model specification

Following the discussion in section 4.2 on the potential mutual dependencies between preferences and behavior, two model specifications are set up to test whether the environment attitudes determine or are determined by car mode share. The path diagrams of the two specifications are shown in Figures 4-3 and 4-4.

Figure 4-3 describes the latent variable model that incorporates the three environmental attitude factors *f_Env*, *f_EnvGov*, *f_EnvTax* in the car mode share model and the causal relationship is assumed to be one way from the environmental attitudes to car mode share.

Figure 4-4 describes the latent variable model that allows two-way causality. The black arrows indicate the feedback from car mode share to the environmental attitudes.

The two specifications can be compared in two ways in order to decide which behavioral hypothesis is more strongly supported by the data: the first is to examine the overall goodness-of-fit statistics to see which specification fits the data better; the second is to test the specific significance of the feedback (the causal link from behavior to attitudes) by examining the t-statistics of the coefficients associated with the dark arrows.

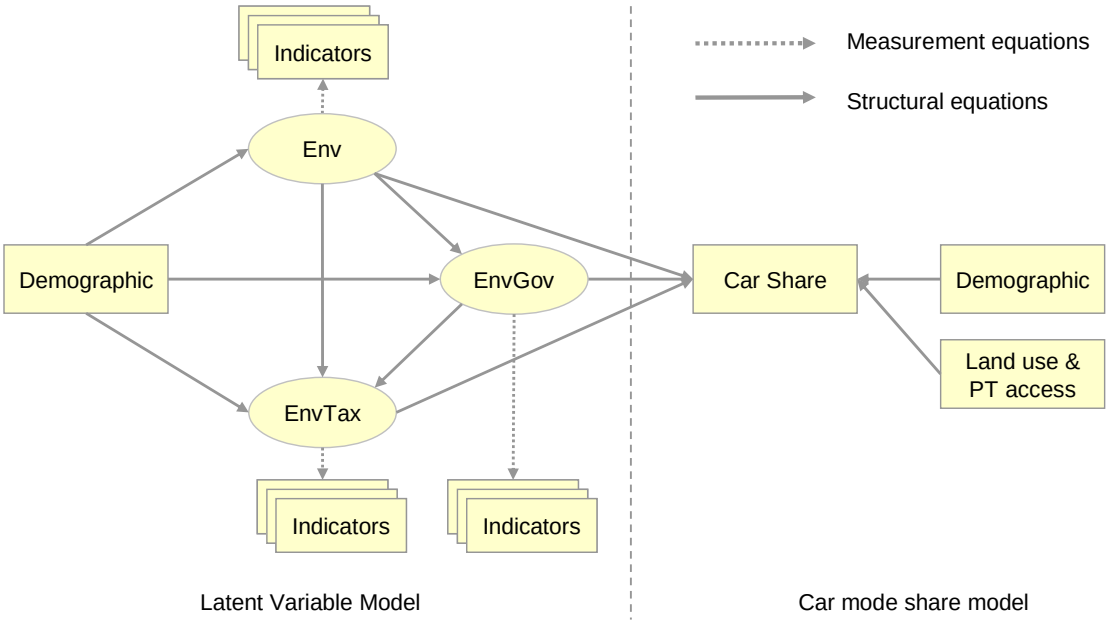


Figure 4-3 Path Diagram of the SEM Model without Feedback

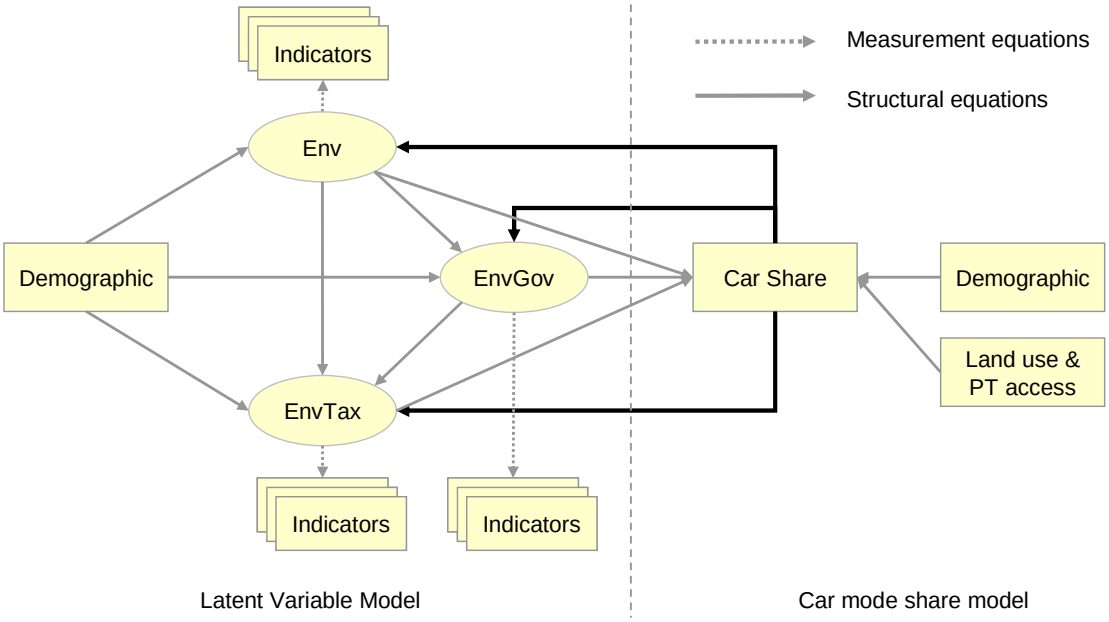


Figure 4-4 Path Diagram of the SEM Model without Feedback

Different sets of exogenous variables (demographics, socioeconomics, land use and PT access) are chosen for the attitudinal endogenous variables (*f_Env*, *f_EnvGov* and *f_EnvTax*) and for the behavioral endogenous variable (Car Share) with the following a priori expectations, which are based on prior literature, findings from the MIMIC model in Chapter 3 and intuitive judgments.

1. Land use patterns and public transport accessibility (D_Pop, ENTROP, PTAL and OUTERL) directly influence car mode share but not environmental attitudes.

2. Employment status and household structure (Working, Student, HavChild, Adult1 and Adult3) directly influence car mode share but not environmental attitudes.

3. Demographic characteristics (Young, Old, Male, British, and SGrade) directly influence environmental attitudes but not car mode share.

4. Car ownership, bike ownership and income have direct effects on both car mode share and environmental attitudes.

There are also differences in the exogenous variable sets among the three attitudinal factors based on the findings from the MIMIC model presented in Chapter 3 (Table 3-13): income is assumed to direct influence *f_EnvTax* but not *f_Env* and *f_EnvGov*; Being British influences *f_Env* but not the other two; Being Young or Old influence *f_Env* and *f_EnvGov* but not *f_EnvTax*.

4.5.2 Model identification

As reviewed in Chapter 2, when there are feedback loops in the SEMs, the identification of the model is not automatically guaranteed. The identification of model specification 2 is checked below applying the two basic necessary conditions as well as the order and rank conditions suggested by Berry (1984):

1) The two basic necessary conditions: first, the degrees of freedom is 269, which is greater than 0; second, each latent variable has at least four indictors and has a scale through the unit loading constraint for the first indicator.

2) Order condition

The number of endogenous variables is 4: *f_Env*, *f_EnvGov*, *f_EnvTax* and CarShare. The number of excluded variables for *f_Env* (variables that do not have direct effects on *f_Env*) is 10; the numbers of excluded variables for *f_EnvGov*, *f_EnvTax*, and CarShare are 12, 11, and 7 respectively. They are all greater than the number of endogenous variables minus 1, which is 4-1=3, so the order condition is met.

3) Rank condition

Table 4-4 and 4-5 show the system matrix of model specification 2 and the reduced matrixes for each of the four endogenous variables

Table 4-5 System Matrix for Model Specification 2

	Env	EnvGov	EnvTax	ShCar	Young	Elder	Male	Sgrade	British	IncX	CarTwo	Bike	Child	Adu1	Adu3	Work	Stud	D_pop	Entrop	PTAL	OuterL
Env	1	0	0	0	1	1	1	1	1	0	1	1	0	0	0	0	0	0	0	0	0
EnvGov	1	1	0	0	1	1	1	1	0	0	1	1	0	0	0	0	0	0	0	0	0
EnvTax	1	1	1	0	0	0	1	1	0	1	1	1	0	0	0	0	0	0	0	0	0
ShCar	1	1	1	1	0	0	0	0	0	1	1	1	1	1	1	1	1	1	1	1	1

Table 4-6 Reduced Matrixes for Model Specification 2

Reduced Matrix for F_Env													
	EnvGov	EnvTax	ShCar	IncX	Child	Adu1	Adu3	Working	Stud	D_pop	Entrop	PTAL	OuterL
EnvGov	1	0	0	0	0	0	0	0	0	0	0	0	0
EnvTax	1	1	0	1	0	0	0	0	0	0	0	0	0
ShCar	1	1	1	1	1	1	1	1	1	1	1	1	1
Reduced Matrix for F_EnvGov													
	EnvTax	ShCar	British	IncX	Child	Adu1	Adu3	Working	Stud	D_pop	Entrop	PTAL	OuterL
Env	0	0	1	0	0	0	0	0	0	0	0	0	0
EnvTax	1	0	0	1	0	0	0	0	0	0	0	0	0
ShCar	1	1	0	1	1	1	1	1	1	1	1	1	1
Reduced Matrix for F_EnvTax													
	ShCar	Young	Elder	British	Child	Adu1	Adu3	Working	Stud	D_pop	Entrop	PTAL	OuterL
Env	0	1	1	1	0	0	0	0	0	0	0	0	0
EnvGov	0	1	1	0	0	0	0	0	0	0	0	0	0
ShCar	1	0	0	0	1	1	1	1	1	1	1	1	1
Reduced Matrix for ShCar													
	Young	Elder	Male	Sgrade	British								
Env	1	1	1	1	1								
EnvGov	1	1	1	1	0								
EnvTax	0	0	1	1	0								

All four reduced matrixes have a rank of 3, which is equal to the number of endogenous variables minus 1, so all four endogenous variables satisfy the rank condition.

Both the two basic necessary conditions and the order and rank conditions are met for model specification 2 so it is identifiable.

4.5.3 Estimation results

Both specifications are estimated in Mplus v5 based on the car owner sample. The measurement equations and the structural equations for the latent factors, and the car mode share model with socioeconomic status, land use and public transport access variables are estimated simultaneously. The results are reported in Tables 4-7 through 4-9.

Table 4-7 compares the goodness-of-fit between the model with and without feedback. Both models provide a good data fit as indicated by the CFI, RMSEA and SRMR statistics. But these statistics as well as AIC, Sample Size Adjusted BIC all suggest that the model with feedback provides a better data fit.

Since specification 1 is a constrained model of specification 2 (constraining all the coefficients from behavior to attitudes to be zero), a chi-square test can be used to test if the more general model is significantly better than the constrained one:

The change of degrees of freedom is 274-271=3. The critical value at the 1% significance level is 11.35. The chi-square difference is 596.3-560.9= 35.4, which is greater than the critical value, rejecting the hypothesis that the models are equivalent. The model with feedback offers a better goodness-of-fit to the data.

Table 4-7 Goodness-of-fit statistics

	Overall Goodness of Fit	
	w/o Feedback	w/ Feedback
Observatior	1287	1287
Chi-Square	596.3	560.9
Loglikelihoc	-34360.3	-34342.6
Degree of F	274	271
CFI	0.926	0.933
AIC	68886.7	68857.3
Sample Size	69051.3	69027.8
RMSEA	0.03	0.027
90% CI of R	0.027~0.034	0.025~0.032
SRMR	0.03	0.027

There are no significant differences between the measurement equations of the two specifications. The factor loadings in both specifications are similar to the ones estimated in the CFA model in Chapter 3 (Table 3-9).

The two specifications also estimate similar relationships among the three latent factors: *f_Env*, *f_EnvGov* and *f_EnvTax*. The feedback from behavior to attitudes does not change the relationships among the three factors. Figure 4-5 shows coefficients estimated in the second specification: two of the three causal links are significant: general pro-environment attitude (*f_Env*) increases the support for government action to protect the environment (*f_EnvGov*), which then increases the willingness to pay taxes in order to do so. The direct link between *f_Env* and *f_EnvTax* is not significant suggesting that the influence of *f_Env* on *f_EnvTax* is mostly mediated through *f_EnvGov*.

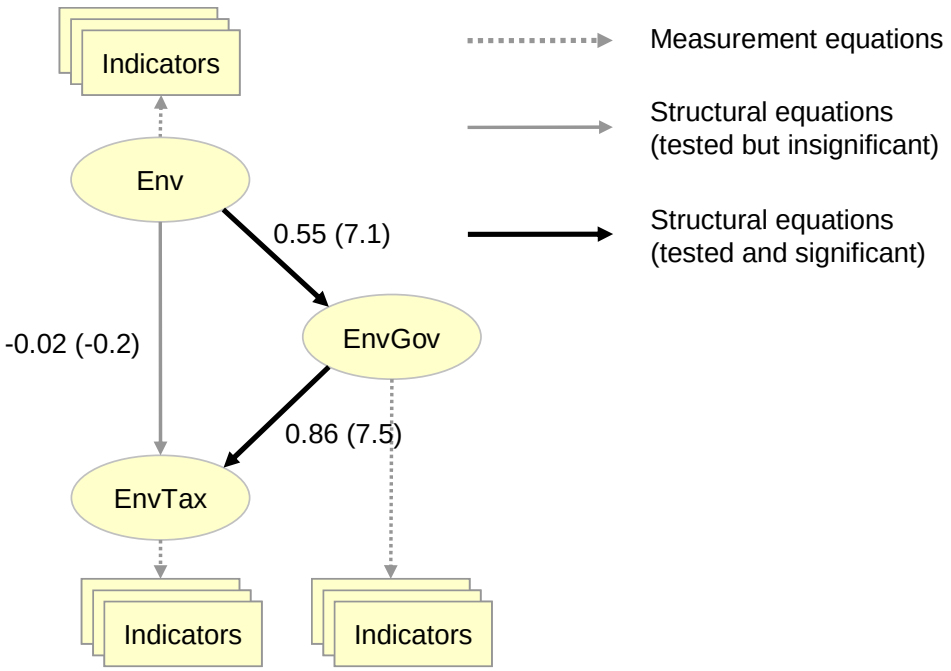


Figure 4-5 Partial Path Diagram among the Latent Factors

The differences between the two models arise in the structural equations between the latent factors and car mode share.

Table 4-8 shows the structural equations for the latent factors in both models. Car mode share (SHCAR) is included in the structural equations for the model with feedback to reflect that these latent factors can be caused by car mode share. Car mode share is significant in two of the three latent factor structural equations: car mode share negatively influences people's support for government action to protect the environment (*f_EnvGov*) and their willingness to pay taxes to do so (*f_EnvTax*).

Table 4-9 compares the structural equations for car mode share in both models. There are significant differences between the two specifications. The latent factors have changed their significance, signs or magnitudes after the feedback from behavior to attitudes are included in the model. The results in Tables 4-6 and 4-7 will be discussed further after we discuss which specification is chosen as the preferred model.

Table 4-8 Structural equations for latent variables

	Model without feedback		Model with feedback	
F_ENV	**Estimate**	**t**	**Estimate**	**t**
YOUNG	**-0.253**	**-4.5**	**-0.278**	**-4.6**
ELDER	**0.168**	**2.7**	**0.160**	**2.6**
MALE	**-0.080**	**-2.1**	**-0.087**	**-2.3**
SGRADE	**0.048**	**3.3**	**0.044**	**2.9**
BRITISH	**-0.161**	**-3.9**	**-0.148**	**-3.6**
CARTWO	-0.058	-1.5	-0.032	-0.7
HAVBIKE	**0.172**	**4.3**	**0.161**	**4.0**
SHCAR	n.a.		-0.276	-1.2
F_GOV	**Estimate**	**t**	**Estimate**	**t**
YOUNG	0.021	0.4	**-0.115**	**-1.9**
ELDER	-0.032	-0.6	-0.037	-0.7
MALE	-0.054	-1.6	**-0.079**	**-2.1**
SGRADE	0.021	1.6	-0.003	-0.2
CARTWO	**-0.131**	**-3.7**	-0.021	-0.5
HAVBIKE	0.026	0.7	-0.011	-0.3
SHCAR	n.a.		**-1.089**	**-4.0**
F_TAX	**Estimate**	**t**	**Estimate**	**t**
MALE	**0.219**	**4.9**	**0.218**	**4.8**
SGRADE	0.027	1.5	0.027	1.5
INCX	0.021	1.5	0.011	0.7
CARTWO	-0.033	-0.7	0.028	0.5
HAVBIKE	**0.096**	**2.2**	0.075	1.6
SHCAR	n.a.		**-0.550**	**-2.9**

Table 4-9 Structural equations for car mode share

Ind. Variables		Model without feedback		Model with feedback	
		Estimate	t	Estimate	t
Latent Variables	F_ENV	**-0.053**	**-2.6**	**-0.245**	**-2.8**
	F_GOV	0.014	0.5	**0.314**	**3.0**
	F_TAX	**-0.047**	**-3.0**	0.078	1.5
Observed Variables	INCX	**-0.013**	**-3.0**	**-0.026**	**-4.1**
	CARTWO	**0.094**	**6.1**	**0.152**	**6.3**
	HAVBIKE	**-0.035**	**-2.5**	**-0.072**	**-3.3**
	HAVCHILD	**0.091**	**6.4**	**0.140**	**6.0**
	ADULT1	**0.044**	**2.2**	**0.058**	**2.1**
	ADULT3	**-0.048**	**-2.9**	**-0.051**	**-2.3**
	WORKING	-0.012	-0.6	-0.033	-1.1
	STUDENT	**-0.123**	**-4.0**	**-0.163**	**-3.5**
	D_POP	**-0.053**	**-2.0**	**-0.093**	**-2.5**
	ENTROP	0.000	0.0	-0.072	-0.5
	PTAL	-0.013	-1.6	**-0.018**	**-1.7**
	OUTERL	0.027	1.4	0.044	1.6

4.5.4 Preferred model specification

The second specification with the feedback causal link is chosen as the preferred model for three reasons:

1) The goodness-of-fit statistics indicate the second model improves the overall data fit from the first model;

2) Car mode share (SHCAR) is significant in the structural equations of the latent factor *f_EnvGov* and *f_EnvTax*

3) Previous literature has demonstrated that mutual dependencies can exist between behavior and attitudes

The following interpretation will be based on the second specification.

4.5.5 Interpreting the causality between environmental attitudes and car mode share

Figure 4-6 shows the final path diagram based on the model results of specification 2. The solid grey arrows refer to the causal links that are assumed to be important but are

rejected by the data. The solid black arrows show the causal links that are confirmed to be important by the data.[4] The coefficients associated with these arrows between the latent factors and car mode share are listed with their t-statistics in parentheses.

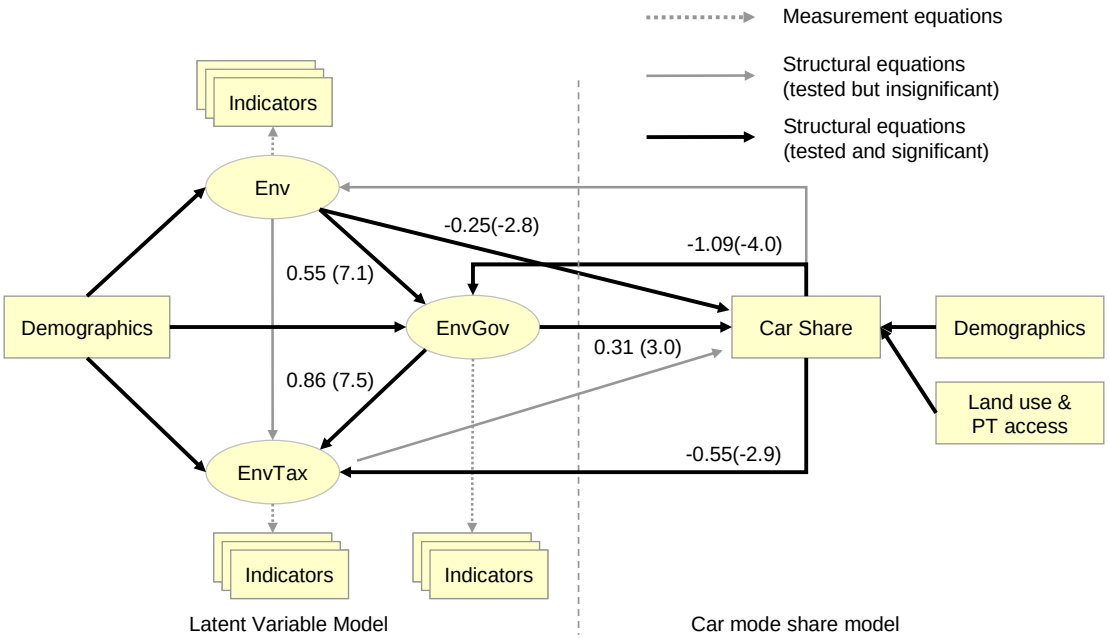


Figure 4-6 Full Path Diagram of the SEM model with Feedback Loop

Interrelationships between car mode share and the environmental attitudes in both directions are identified. On one hand, positive environmental attitude results in lower car mode share. On the other hand, high car mode share reduces people's support for government's environmental protection actions and willingness to pay taxes for this purpose. One surprising finding is that *f_EnvGov* has a positive influence on car mode share. Possible multicollinearity among *f_Env*, *f_EnvGov* and *F_EnvTax* is considered but ruled out. The common detection method of the variance inflation factor (VIF) may not be applicable in the model with feedback loop. But a model with only *f_EnvGov* and CarShare as two endogenous variables is tested and it is found that the positive effect of *f_EnvGov* on Car Share remains. Further investigation is required to understand this counter-intuitive result.

[4] There are multiple variables in the demographic group and land use and PT access group. To simplify the diagram they are shown only by their groups. As long as at least one variable is significant, the arrow is shown in solid black.

4.6 Car Mode share and Personality Traits

This section examines the relationships between car mode share and two personality traits: liking to be in control (*f_InCtrl*) and being extrovert (*f_Extro*). Similar to Section 4.4, two specifications are tested in Mplus: one with one way causal links from personality to car mode share; the other with causal links in both directions.

Table 4-10 compares the goodness-of-fit of the two models. In both models CFIs are below 0.9 but RMSEA and SRMR statistics are below 0.05 and the entire 90% confidence intervals of RMSEA are below 0.05. Overall both models offer a reasonably good data fit.

The improvement to the goodness-of-fit statistics in the model with feedback is not significant. A chi-square test cannot reject the hypothesis that the models are equivalent. (The change of degrees of freedom is 2. The critical value at the 1% significance level is 9.21. The chi-square difference is 4.2, smaller than the critical value).

Therefore the model without feedback is preferred for its simplicity. Figure 4-7 shows the path diagram with the significant causal links. The grey curved arrow between *f_InCtrl* and *f_Extro* indicates the correlation between the two factors is not significant. The impact of being extrovert on car mode share is not significant. But being in control has a significant negative impact on car mode. This is consistent with the findings in the mode choice models in Chapter 5, which finds that *f_InCtrl* increases the probability of using public transportation compared to car. To use public transport effectively often requires travelers to plan things ahead and to control your schedule carefully in order to catch the desired train or bus. Therefore being in control increases the chance to use public transit and reduce car mode share. But an opposite argument is also plausible that driving a car provides travelers a stronger feeling of being in control therefore *f_InCtrl* should increase the car mode share. Please see Chapter 5 for further discussion on this.

Table 4-10 Goodness-of-fit statistics

	Overall Goodness of Fit	
	w/o Feedback	w/ Feedback
Observations	1287	1287
Chi-Square	711.1	706.9
Loglikelihood	-31980.7	-31978.6
Degree of Freedom	253	251
CFI	0.820	0.821
AIC	64105	64105
Sample Size AdjustedBIC	64248	64252
RMSEA	0.038	0.038
90% CI of RMSEA	0.034~0.041	0.034~0.041
SRMR	0.035	0.035

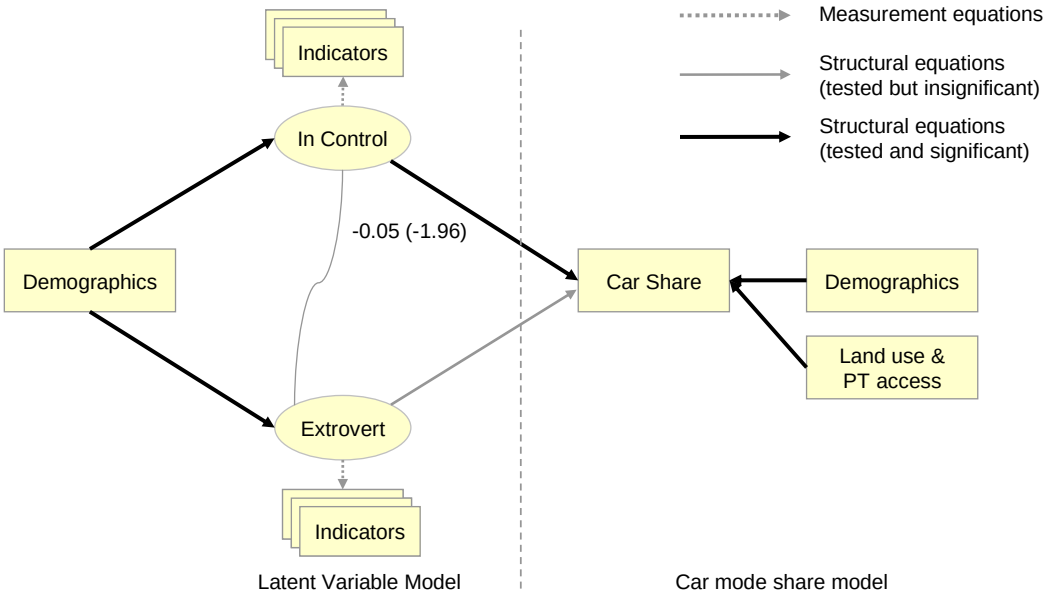


Figure 4-7 Path Diagram for the Relationships between Personality and Car Mode Share

4.7 Car Mode Share and Car Pride

This section examines the relationships between car pride, perceptions of convenience and comfort, and car mode share. Models with and without feedback from car mode share to latent factors are estimated. As shown in Table 4-11, the model with feedback significantly improves the goodness-of-fit. With three more parameters, the model with

feedback decreases the chi-square by 12.3, which is above the critical value of 11.35 at the 1% significance level.

Table 4-11 Goodness-of-fit statistics

	Overall Goodness of Fit	
	w/o Feedback	w/ Feedback
Observations	1287	1287
Chi-Square	362.9	350.5
Loglikelihood	-31273.2	-31267.0
Degree of Freedom	254	251
CFI	0.971	0.974
AIC	62696	62690
Sample Size Adjusted BIC	62845	62845
RMSEA	0.018	0.018
90% CI of RMSEA	0.014~0.022	0.013~0.022
SRMR	0.025	0.023

Figure 4-8 shows the significant causal links with their coefficients and t-statistics. Car mode share has significantly positive impact on the perception of car convenience. The causal links from convenience and comfort to car pride are also significant. But the impacts of the three latent factors on car mode share are not significant. The t-statistic of the impact of car pride on car mode share is 1.55, which is marginally significant.

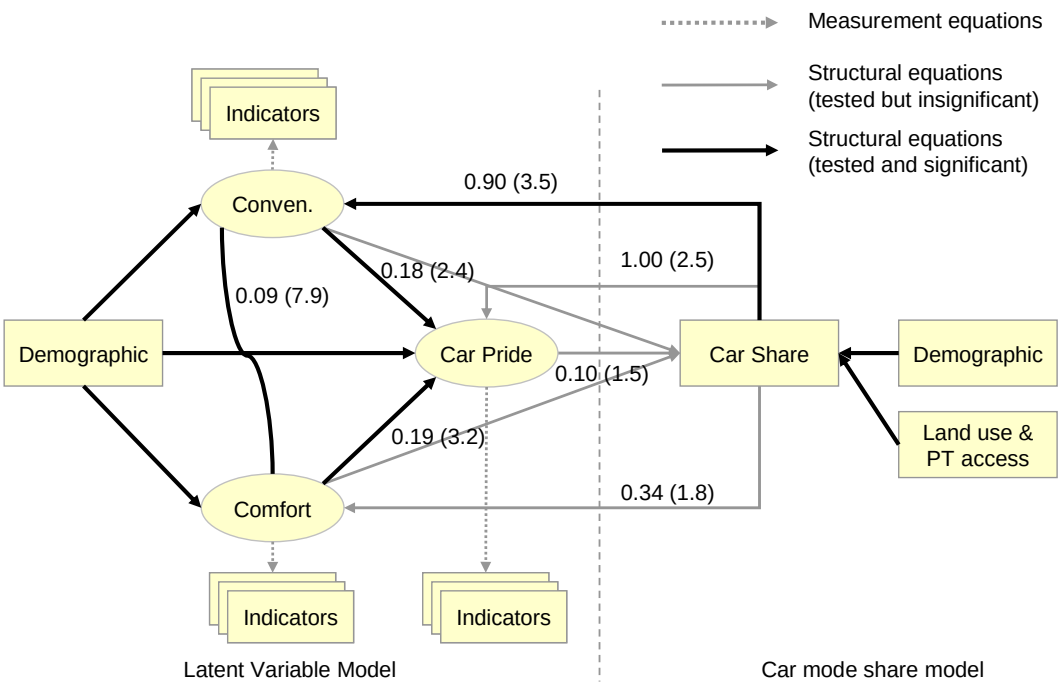


Figure 4-8 Path Diagram for the Relationships between Car Mode Share and Car Pride and Perceptions

4.8 Different Roles of Latent Factors in Car Share and Frequency Models

Three sets of SEMs are also estimated with car trip frequency as the dependent variable: one for each set of the latent traveler preferences including environmental attitudes, personality traits, car pride and perceptions of convenience and comfort.

Similarly to sections 4.5, 4.6 and 4.7, to examine the mutual relationships between car trip frequency and traveler preferences, models with and without feedback from behavior to preferences are estimated and compared.

Table 4-12 compares the overall data fit between models with and without feedback for the six sets of SEM models (three for car mode share and three for car trip frequency). In three of the six sets, chi-square tests reject the hypothesis that the models with and without feedback are equivalent, suggesting the feedback from behavior to preferences results in significant improvement of the goodness-of-fit. In the other three sets of

models, the feedback from behavior to preferences is not significant. Specifically in both models with the personality traits, the feedbacks from travel behavior do not significantly influence personality.

Table 4-12 Overall Data Fit Comparison

Latent Factor Groups	Chi-Square Test	Car Mode Share		Car Trip Frequency	
		without Feedback	with Feedback	without Feedback	with Feedback
Environmental Attitudes	Chi-Square	596.3	560.9	548.1	541.9
	Degree of freedom	272	269	259	256
	Test result	Reject		Cannot Reject	
Personality Traits	Chi-Square	711.1	706.9	713.5	709.4
	Degree of freedom	253	251	254	252
	Test result	Cannot Reject		Cannot Reject	
Car Pride + Perceptions	Chi-Square	362.9	350.5	333.7	323.7
	Degree of freedom	254	251	241	238
	Test result	Reject		Reject	

Table 4-13 summarizes the significance of the causal links between behavior and preferences for each of the eight latent factors in the SEMs. There are four possible relationships between behavior and preference: 1) behavior shapes preferences but preferences do not influence behavior; 2) preferences influence behavior but behavior does not shape preferences; 3) behavior and preference are mutually dependent; 4) behavior and preferences do not influence each other in either direction. All four possible relationships exist among the combinations of the three sets of preference factors and the two aspects of travel behavior. Broadly speaking, in the models with personality traits, the dominant causal direction is that preferences influence behavior; in the model of car pride and perceptions, behavior shaping preferences dominates the causality; in the models of environmental attitudes, car mode share and car trip frequency have distinct patterns: for car mode share, relationships between behavior and preferences in both directions are significant; for car trip frequency, causalities from both directions are either not significant or weak.

Table 4-13 Significance of the Causal Links between Behavior and Preferences

Latent Factors		Car Mode Share		Car Trip Frequency	
		B --> P	P --> B	B --> P	P --> B
Environmental Attitudes	f_Env	None	Strong	None	Weak
	f_EnvGov	Strong	Strong	None	None
	f_EnvTax	Strong	None	None	Weak
Personality Traits	f_InCtrl	Strong*	Strong	None	Strong
	f_Extro	None	None	None	Strong
Car Pride + Perceptions	f_CarPride	None	None	Strong	None
	f_Conven	Strong	None	None	None
	f_Comfort	Weak	None	None	None

Notes

B --> P: Behavior causes preferences

P --> B: Preferences causes behavior

Strong: Significant at 5% level

Weak: Significant at 10% level but not at 5% level

None:Insignificant at 10% level

* For the relationships between personality and car share, we cannot reject that the models with and without feedback are equivalent but the coefficient of the individual effect of f_InCtrl on car mode share is significant

4.9 Direct and Indirect Effects of the SES Variables on Car Mode Share

When latent variables are introduced into the car mode share or car trip frequency models, the SES variables can potential have two different impacts on the car mode share or car trip frequency: one is the direct impact and the other is the indirect impact via the latent variables.

The SEM specifications can distinguish between the direct and indirect effects of SES variables on travel behavior and estimate their directions and magnitudes statistically. Take the SEM model for car mode share with environmental attitudes (path diagram shown in Figure 4-7) as an example. Figure 4-9 illustrates two ways in which the dummy variable of having a bike can influence the car mode share. The coefficients and the t-statistics associated with each are obtained from the structural equations for the latent factors and the car mode share of the SEM model with feedback. Both effects are statistically significant.

The first is the direct effect: having a bike decreases car mode share. The second is the indirect effect via the latent factor *f_Env*: having a bike improves the environmental attitude, which in turn decreases car mode share. So the effect of the full path from having a bike to *f_Env* to car share is negative. The total effect of having a bike on car share is the sum of the direct and indirect effects.

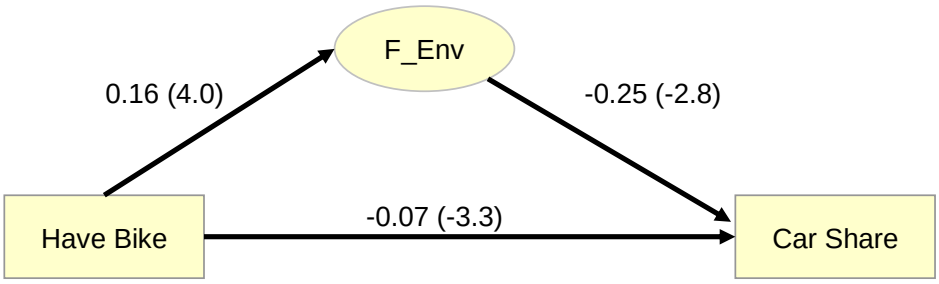


Figure 4-9 Direct and Indirect Effects of having a bike on Car Mode Share

4.10 Summary

The chapter examined the relationship between traveler preferences and car use. Both car mode share and car trip frequency are tested as two aspects of car use.

The structural equation models effectively quantify the eight latent factors and incorporate them into the car use models.

Two specifications are tested: one assumes one way relationships from preferences to behavior, and the other assumes two-way relationships by incorporating feedback from behavior to preferences. The mutual dependencies between behavior and preferences are identified. Overall behavior influences more than is influenced by preferences. But the exact direct and strengthen of the causality vary by the latent factor and by aspects of travel behavior.

Direct and indirect effects of the SES variables on car mode share are distinguished by introducing the latent factors into the model. There are substantial changes (significance, sign, or magnitude) in the coefficients of the SES variables in the car mode share equation between models with and without latent factors. Without latent

variables, the models may produce biased estimates for the coefficients of those socioeconomic and demographic variables that have indirect effect on car mode share. This is a type of missing variable bias but in this case, the missing variables are latent.

By incorporating the latent factors, the models expand our understanding of car use from the traditional areas of socio-economic status, land use and public transportation to the cultural and psychological domains such as personality traits, environmental attitudes and car pride.

Chapter 5. Traveler Preferences in Disaggregate Mode Choice

This chapter applies the proposed structure of traveler preferences to mode choice at the disaggregate level. The discrete choice analysis methods are the backbone of most transportation models in practice so it is particularly important to examine traveler preferences in the discrete choice context.

Recent innovations in discrete choice methodologies have also enabled a more thorough examination of traveler preferences, including latent variable models (Ben-Akiva, Walker et al 1999, Morikawa et al 2002, Ashok et al 2002, Temme et el 2008, Vredin Johansson, Heldt, and Johansson 2006, McFadden 1986), latent class models (Gopinath 1995, Bhat 1997, Swait 1994, Hensher and Greene 2003), and flexible error structure models (Ben-Akiva and Bolduc 1996, McFadden and Train 2000, Bhat 1997) among other important enhancements. Walker and Ben-Akiva (2002) present a generalized random utility model which integrates these extensions within a single methodological framework.

Full scale applications of this framework incorporating a rich set of latent constructs, combining latent variable and latent class, and estimating the choice model, latent variable model and latent class model simultaneously, remain rare. Johansson et al (2006), Choo and Mokhtarian (2004), Ashok et al (2002), Walker and Li (2006) and Temme et al (2008) are a few examples applying certain portions of this framework.

This chapter applies this generalized random utility model to examine the impact of Londoners' personality traits, environmental attitudes, car pride and perceptions of convenience and comfort on mode choice. The study also examines the unobserved heterogeneity in Londoners' sensitivities to these latent constructs and incorporates latent variables in the latent class membership model.

A series of nine models are presented in Table 5-1, starting with the baseline MNL model with six travel modes as the choice set and SES variables and alternative attributes as the explanatory variables, followed by four latent variable choice models that incorporate up to six latent variables with parallel and hierarchical interrelationships, and finally four latent class models that examine the unobserved heterogeneities of traveler preferences and test a few hypotheses of how the socio-demographic and attitudinal characteristics of the travelers influence these heterogeneities.

Table 5-1 Summary of Models

Types	Models
MNL Model	Model 1 Baseline MNL Model
Latent Variable Models	Model 2 Choice Model with the "Car Pride" Latent Factor
	Model 3 Choice Model with the "Environmental Attitude" Latent Factor
	Model 4 Choice Model with Multiple Latent Factors
	Model 5 Choice Model with Multiple Latent Factors and Hierarchical Relationships
Latent Class Models (with latent variables)	Model 6 Latent Class Model with Heterogeneity in the Sensitivity to Travel Time
	Model 7 Latent Class Model with Heterogeneity in the Sensitivity to the "Convenience" Latent Factor
	Model 8 Latent Class Model with the Class Membership Defined by the "Extrovert" Latent Factor
	Model 9 Latent Class Model with Heterogeneity in the Sensitivity to the "Convenience" Latent Factor and the Class Membership defined by the "Car Pride" Latent Factor

The chapter is organized as follows. Section 5.1 describes the data processing and variable definition; section 5.2 presents the traditional MNL model which is the baseline for comparison with the enhanced models; section 5.3 presents the four latent variable models; section 5.4 presents the four latent class models including those combining latent class and latent variable models; and section 5.5 summarizes the findings.

5.1 Data Processing and Variable Definition

In addition to the socio-economic status and the 102 attitudinal and perceptual statements, a partial travel diary for one randomly chosen day is reported by the respondents to the London Lifestyle and Car Dependency Survey including two randomly chosen trips out of all the trips they made that day. The trip information

includes trip duration, trip purpose, trip origin and destination, and the time of day. The final sample includes 2147 trips.

Six modes of travel are modeled: walking, cycling, train[5], bus, car driver and car passenger. Car driver is chosen as the reference mode in all models so behavioral findings are expressed relative to the car driver mode.

Four categories of variables are included in the models:
1) Travel time, trip purpose (seven trip purposes are defined: work, education, escorting children to school, leisure, shopping, personal business and other) and time of day (six time periods are defined: early morning, AM peak, inter-peak, PM peak, evening and late night)

The travel time of alternative modes are estimated based on a regression model of the average travel speeds, which are differentiated by modes, time of day, gender and age, trip purposes, trip length, and trip origin and destination. Appendix B reports the details of the speed regression model.

2) Vehicle ownership and socio-economic and demographic characteristics of the traveler

3) Land use patterns and public transportation accessibility

The variables in categories 2 and 3 are defined as in chapter 3.

4) Latent factors are personality traits, environmental attitudes, car pride, and perceptions of convenience and comfort of car relative to transit

The latent factors are measured by the same sets of indicators as specified in chapter 3 but the coefficients of the latent variable measurement equations are estimated simultaneously with the coefficients of the discrete choice part of the models.

[5] National Rail and London Underground are merged and considered as one mode: train.

The baseline model includes variables in groups 1, 2 and 3 while all other models also include group 4.

5.2 Baseline MNL Mode Choice Model

A typical MNL mode choice model with six alternatives is estimated as the baseline for comparison purposes. The model is estimated both in Biogeme v1.8 and Mplus v5 with identical estimation results. Tables 5-2 and 5-3 summarize the model fit and the coefficient estimates of the MNL model. The overall model fit is reasonable with a pseudo R-square of 0.26.

Table 5-2 Goodness-of-Fit for Baseline MNL Model

Model Fit Summary	
Obs	2147
LogLikelihood	-2509.6
Null Loglikelihood	-3388.7
#Parameters	68
#Para (Null Model)	5
Pseudo R-square	25.9%
Pseudo R-square Adj	24.1%

The travel time coefficients are allowed to vary across modes and all have the correct (negative) signs. Owning cars significantly decreases the probability of using all other modes, particularly bus, but to a lesser extent car passenger. In contrast, owning a bike increases the probability of walking, potentially because owning a bike indicates a more active life style, which includes more walking.

The six trip purpose dummies (six dummy variables are used for seven trip purposes. “Other purposes” is chosen as the reference) are tested in various combinations with five of six travel modes (The car driver mode is the reference and is not interacted with the dummies). Table 5-3 lists the significant ones:

1) Everything else being equal, walking is favored for all purposes but going to work; cycling is more likely to be used for commuting to work and to school than other purposes

2) Train is preferred for commuting to work or to school and leisure trips; bus is favored for school trips but not for parents escorting their children

3) Traveling as car passengers is preferred for leisure trips and not for commuting to work or escorting children to school

From the perspective of the time of day, the only two significant deviations from the average are that people walk more in the morning peak hours and travel more as car passengers in the evening.

The model also captures a series of observed degrees of heterogeneity in traveler preferences by their socioeconomic and demographic characteristics:

1) Everything else being equal, the young are more likely to use public transportation as well as ride as car passengers; the old are less likely to travel by train or as car passengers; males are less likely to travel by bus or as car passengers than females;

2) The British use bus less than other ethnic groups;

3) People of higher social grade are more likely to travel by train; working people are less likely to travel by bus, as car passengers, or on foot.

4) Single people are less likely to travel by train, as car passengers, or on foot; having children decreases the probability of traveling by train; families with three or more adults are more likely to use public transport or share rides.

The impacts of land use patterns are as expected: high density and land use mix increase bus use. Greater mix also encourages ride sharing and walking. Outer London residents are less likely to walk, cycle or use buses. In general public transport accessibility increases public transport usage but access to train stations increases train use and decreases bus use.

The above findings are no surprise and they serve as the basis for comparison with the more advanced models that follow.

Table 5-3 Baseline MNL Model Results

Mode	Walk	Beta	t	Cycle	Beta	t	Train	Beta	t	Bus	Beta	t	Car Passenger	Beta	t	Car Driver	Beta	t
Travel Time	TT_WALK	-5.39	-14.0	TT_CYCLE	-4.67	-7.3	TT_TRAIN	-3.89	-10.0	TT_BUS	-5.32	-12.4	TT_PASS	-6.70	-11.0	TT_DRIVE	-6.37	-10.9
Trip Purpose	PURWORK	-0.60	-2.9	PURWORK	1.20	3.6	PURWORK	0.80	5.2				PURWORK	-1.18	-4.4	Reference Case		
	PUREDU	1.51	3.5	PUREDU	2.30	2.8	PUREDU	1.86	4.6	PUREDU	1.78	4.5						
										PURESCO	-2.22	-3.7	PURESCO	-1.79	-3.3			
	PURLEI	0.75	3.5				PURLEI	0.91	4.6				PURLEI	0.67	3.1			
	PURSHOP	0.73	3.9															
	PURPRNL	0.75	2.4															
Time of Day	TIMEAM	0.54	3.4															
													TIMEEVE	0.69	3.1			
Vehicle Ownership	HAVBIKE	0.42	3.1															
	CARS	-1.38	-11.4	CARS	-1.23	-5.2	CARS	-1.33	-10.9	CARS	-1.93	-14.8	CARS	-1.01	-6.9			
Socioeconomic & demographic							YOUNG	0.39	1.7	YOUNG	0.97	4.4	YOUNG	0.60	2.4			
							OLD	-0.84	-2.9				OLD	-0.98	-2.6			
										MALE	-0.41	-3.0	MALE	-1.16	-5.9			
										BRITISH	-0.44	-3.2						
	WORKING	-0.42	-2.4							WORKING	-0.43	-2.3	WORKING	-0.45	-2.1			
	ADULT1	-0.41	-2.4				ADULT1	-0.42	-2.3				ADULT1	-0.98	-3.5			
							ADULT3	0.61	3.7	ADULT3	0.45	2.6	ADULT3	0.47	2.3			
							HAVCHILD	-0.42	-2.9									
							SGRADE	0.12	2.2									
							STUDENT	0.54	1.8									
Land Use										D_POP	0.42	1.8						
	ENTROPY	2.11	2.1							ENTROPY	1.77	1.7	ENTROPY	2.58	1.9			
	OUTERL	-0.61	-4.1	OUTERL	-0.95	-3.1				OUTERL	-0.78	-4.3						
							PTAL	0.16	2.7	PTAL	0.12	1.5						
							ACCTRAIN	0.71	5.2	ACCTRAIN	-0.52	-3.6						
ASC	ASC1	0.84	1.0	ASC2	-1.62	-3.8	ASC3	-1.12	-3.4	ASC4	1.74	1.9	ASC5	-1.11	-1.0			

5.3 Mode Choice Models with Latent Variables

The first enhancement to the MNL model is to include latent constructs such as personality traits, environmental attitudes, car pride and perceptions of convenience and comfort to examine if they play a significant role in explaining people's mode choice.

As discussed in Chapter 1, the causal relationship is assumed to be one way from preferences to mode choice. Mutual dependencies between mode choice and traveler preference are not tested in this chapter.

Four models are presented here: the first two include one latent variable in each model, in Model 2 car pride, and Model 3 environmental attitude. The last two include the six latent variables: two personality factors, two environmental attitudinal factors and two perceptual factors. Model 4 incorporates the latent variables in parallel into the utility function and model 5 preserves the hierarchical relationship among the latent factors while integrating them into the choice model.

5.3.1 Model 2: Choice model with car pride

The first latent variable model examines the impact of the sense of car pride on mode choice. As illustrated in Figure 5-1, the latent factor "car pride" is measured by four indicators and connected to the SES variables in the structural equations in the latent variable part of the model, and the choice model part includes the latent variable as well as all the independent variables in the MNL model. The latent variable and the choice parts of the model are estimated simultaneously in Mplus 5.1. Maximum likelihood estimation with robust standard errors is used.

Tables 5-4 and 5-5 give the estimation results of the measurement and structural equations for the latent factor *f_CarPride*. The indicators for the latent factors are all highly significant. The coefficient of the first indicator is fixed to be 1 for identification purpose as is reflected in the t-statistic of 999.0. The structural equations show that

males have a smaller sense of car pride than females, those who are single feel it more strongly, those who have children or good public transportation access feel it less while those who own cars feel it more.

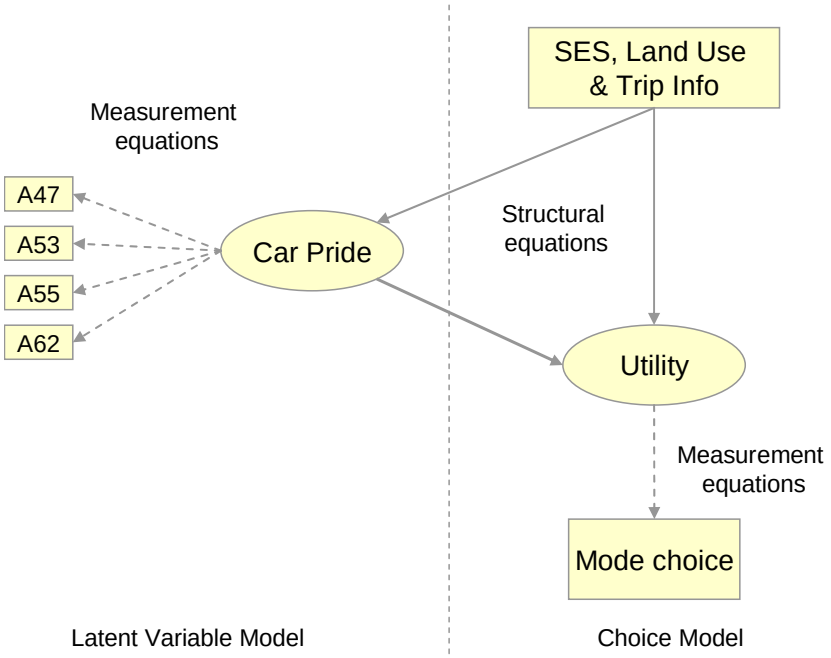


Figure 5-1 Path Diagram of the Latent Variable Choice Model

Table 5-4 Measurement equations for the car pride latent factor

Indicators	Beta	t
A47	1	999.0
A53	0.761	15.8
A55	1.101	20.7
A62	0.947	18.8

The lower section of Table 5-6 lists the coefficients of the “car pride” latent factor in the mode choice utility function. For all five modes relative to driving a car, the coefficients of the car pride factor are significant or marginally significant in the case of car passenger. All have the expected negative signs, since a higher sense of car pride will decrease the probability of using modes other than car. Interestingly car pride also has a negative influence on the probability of traveling as a car passenger, even though it is not as strong an influence as on walking, cycling or public transport, because traveling as a car passenger loses some of the advantage of car travel and does not fully express the sense of car pride.

Table 5-5 Structural equations for the car pride latent factor

SES	Beta	t
YOUNG	0.068	1.3
OLD	-0.038	-0.7
MALE	-0.082	-2.5
CHRIST	0.021	0.6
BRITISH	-0.046	-1.2
SGRADE	0.01	0.8
ADULT1	0.096	2.1
ADULT3	-0.019	-0.4
HAVCHILD	-0.071	-2.0
CARS	0.256	8.9
HAVBIKE	-0.045	-1.3
D_POP	-0.004	-0.1
ENTROPY	0.117	0.5
PTAL	-0.067	-3.4
OUTERL	0.024	0.5

R-Square	Beta	t
f_CarPride	0.101	6.3

The upper section of Table 5-6 gives the coefficients of the observed variables in the choice utility function. Comparing them to Table 5-3, the coefficients generally remain stable with only slight changes in their magnitudes. One exception is the coefficient of the variable “CARS”, the number of cars owned by the household, whose magnitude decreases consistently across all five modes relative to car driver. The structural equations in Table 5-5 indicate that owning cars increases car pride. In model 2, the indirect effect of car ownership on mode choice via car pride is captured explicitly by the latent variable. Therefore the coefficients in Table 5-6, which reflects the direct effect of car ownership on mode choice, are smaller in magnitude than those in Table 5-3, which include both the indirect and direct effects of owning cars on the probability of using them.

Table 5-6 Choice Model with the Car Pride Latent Factor

Observed Variables	Walk	Beta	t	Cycle	Beta	t	Train	Beta	t	Bus	Beta	t	Car Passenger	Beta	t	Car Driver	Beta	t
Travel Time	TT_WALK	-5.41	-8.7	TT_CYCLE	-4.69	-7.4	TT_TRAIN	-3.98	-9.7	TT_BUS	-5.36	-10.7	TT_PASS	-6.85	-10.3	TT_DRIVE	-6.524	-10.1
Trip Purpose	PURWORK	-0.63	-3.1	PURWORK	1.17	3.5	PURWORK	0.78	5.0				PURWORK	-1.19	-4.5	Reference mode		
	PUREDU	1.56	3.3	PUREDU	2.37	2.8	PUREDU	1.91	4.1	PUREDU	1.83	4.1						
										PURESCO	-2.23	-3.7	PURESCO	-1.80	-3.2			
	PURLEI	0.75	3.3				PURLEI	0.92	4.6				PURLEI	0.67	3.2			
	PURSHOP	0.69	3.6															
	PURPRNL	0.70	2.1															
Time of Day	TIMEAM	0.53	3.2															
													TIMEEVE	0.69	3.1			
Vehicle Ownership	HAVBIKE	0.41	3.0															
	CARS	-1.27	-11.0	CARS	-1.09	-4.4	CARS	-1.24	-10.6	CARS	-1.83	-14.3	CARS	-0.96	-6.9			
Socioeconomic & demographic							YOUNG	0.41	1.7	YOUNG	0.99	4.2	YOUNG	0.63	2.5			
							OLD	-0.85	-2.9				OLD	-0.96	-2.5			
										MALE	-0.42	-3.0	MALE	-1.16	-5.7			
										BRITISH	-0.45	-3.2						
	WORKING	-0.44	-2.4							WORKING	-0.44	-2.2	WORKING	-0.46	-2.1			
	ADULT1	-0.37	-2.2				ADULT1	-0.39	-2.2				ADULT1	-0.97	-3.3			
							ADULT3	0.60	3.8	ADULT3	0.44	2.4	ADULT3	0.48	2.4			
							HAVCHILD	-0.44	-3.1									
							SGRADE	0.12	2.5									
							STUDENT	0.58	2.0									
Land Use										D_POP	0.44	1.9						
	ENTROPY	2.12	2.1							ENTROPY	1.77	1.6	ENTROPY	2.56	1.7			
	OUTERL	-0.60	-4.0	OUTERL	-0.95	-3.1				OUTERL	-0.77	-4.3						
							PTAL	0.15	2.4	PTAL	0.11	1.3						
							ACCTRAIN	0.71	5.3	ACCTRAIN	-0.51	-3.5						
ASC	ASC1	0.89	1.1	ASC2	-1.60	-3.5	ASC3	-1.07	-3.2	ASC4	1.80	1.9	ASC5	-1.04	-0.8			

Latent Variables	Walk	Beta	t	Cycle	Beta	t	Train	Beta	t	Bus	Beta	t	Car Passenger	Beta	t	Car Driver	Beta	t
Car Pride	**Car Pride**	**-0.65**	**-4.5**	**Car Pride**	**-0.80**	**-2.6**	**Car Pride**	**-0.54**	**-3.9**	**Car Pride**	**-0.59**	**-3.8**	**Car Pride**	**-0.34**	**-1.8**	Reference Mode		

The loglikelihood value of the final model and the null models are reported in Table 5-7. Because of the inclusion of the latent factor, the loglikelihood value for Model 2 includes both the elements from the choice model and the latent variable model, so the value is not comparable to the one for the MNL model. The pseudo R-square is calculated as the difference between the loglikelihood in the full model and that in the null2 model divided by the loglikelihood in the base null model. The adjusted pseudo R-square increases slightly from 0.241 in the MNL model to 0.245 in the latent variable model.

The null1 model is a constrained model of the full model, so the likelihood ratio test can be used to examine whether introducing *f_CarPride* significantly improves the goodness-of-fit of the model. The change in degrees of freedom is 100-95=5. The critical chi-square value at 1% significance level is 15.09. The test statistic is 2*((-11381.1)-(-11397.2)) =32.2, which is greater than the critical value. Therefore we reject the hypothesis that the constrained and unconstrained models are equivalent. The model with the latent factor *f_CarPride* provides a significant improvement to the model fit.

Table 5-7 Goodness-of-Fit Statistics for Model 2

Model ID	**2.2**
Latent Factor	Car Pride
# of Observations	2147
Loglikelihood of the Full Model	-11381.1
# of Parameters of the Full Model	100
Loglikelihood of Null1 Model	-11397.2
# of Parameters of the Null1 Model	95
Loglikelihood of Null2 Model	-12276.4
# of Parameters of the Null2 Model	32
Base Null LL	-3382.7
Pseudo R-square	0.265
Pseudo R-square (Adjusted)	0.245

Notes:
Null1 is the model in which latent variable coefficients are constrained to be zero;
Null2 is the model in which both latent variable coefficients and observed variable coefficients are constrained to be zero;
Base Null Model is the baseline MNL Model.

5.3.2 Model 3: Choice model with environmental attitude

The second latent variable model examines the impact of environmental attitudes on mode choice. The model structure and estimation are the same as for model 2. The latent factor measurements are strong (Table 5-8) and the structural equations list the SES variables that are significant in influencing the environmental attitude (Table 5-9). Notably being young or single or owning cars negatively impacts environmental attitudes.

Table 5-8 Measurement equations for the environmental attitude latent factor

Indicators	Beta	t
A10	1.000	999.0
A12	0.950	12.5
A13	0.962	11.4
A14	0.827	13.2
A16	1.028	14.8

Table 5-9 Structural equations for the environmental attitude latent factor

SES	Beta	t
YOUNG	-0.303	-6.2
ELDER	0.208	3.8
MALE	-0.046	-1.5
CHRIST	0.056	1.8
BRITISH	-0.143	-4.4
SGRADE	0.048	4.4
ADULT1	-0.122	-2.7
ADULT3	0.016	0.5
HAVCHILD	0.053	1.5
CARS	-0.131	-5.5
HAVBIKE	0.220	6.7
D_POP	-0.014	-0.3
ENTROPY	-0.175	-0.8
PTAL	-0.001	0.0
OUTERL	-0.093	-2.3

R-Square	Beta	t
F_ENV	0.132	7.394

The lower section of Table 5-10 lists the coefficients for the environmental attitude latent factor in the choice utility function. A higher commitment to the environment increases the probabilities of cycling and using the train. Cycling in particular seems the strongest demonstration of environmental commitment in terms of daily travel.

Comparing the upper section of Table 5-10 with Table 5-3 reveals three notable changes among the otherwise stable sets of coefficients:

1) The coefficient of the variable CARS for the cycling mode changes from -1.23 to -1.06, a 14% reduction in magnitude. This is because of the indirect effect of “CARS” on the probability of cycling via the latent environmental attitude, which is similar to the indirect effect observed in Model 2, except that the impact of “CARS” on environmental attitude is negative while that on car pride is positive.

2) The coefficient of the dummy YOUNG for train increases by 21% from 0.39 to 0.47. On average, the young are less environmentally inclined compared to other age groups as suggested by the structural equations for the latent variable, and environmental attitude is positively correlated with the probability of using train, so the indirect effect of being young on train use via the environmental attitude is negative. In the MNL Model 1, the positive direct effect of being young on train use is partially offset by its negative indirect effect via the environmental attitude, and the coefficient which reflects both the direct and indirect effects is estimated as 0.39. In contrast, the latent variable model gives the coefficient as 0.47, which reflects just the direct effect of being young on train use.

3) The alternative-specific constant (ASC) for the cycling mode (ASC2) changes from -1.62 in the MNL Model to -2.36 in the latent variable model, while other ASCs are stable. A negative ASC reflects that everything else being equal, people are less likely to cycle than to drive. The latent variable model estimates an even bigger difference between cycling and driving, because a positive environmental attitude increases the probability of cycling relative to driving, and the latent variable model considers the positive impact of environmental attitude on cycling probability explicitly, and therefore

isolates it from the alternative specific constant for cycling, which makes ASC2 even more negative.

Table 5-11 summarizes the data fit of the model with latent factor “environmental attitude”. Similar to the model with car pride, the improvement of the overall data fit from the MNL model is small with the adjusted pseudo R-square increasing from 0.241 to 0.247. But the likelihood ratio test between the null1 model and the full model rejects the hypothesis that the constrained and unconstrained models are equivalent. The model with the latent factor *f_Env* provides a significant improvement to the model fit.

Table 5-10 Choice model with the environmental attitude latent factor

Observed Variables	Walk	Beta	t	Cycle	Beta	t	Train	Beta	t	Bus	Beta	t	Car Passenger	Beta	t	Car Driver	Beta	t
Travel Time	TT_WALK	-5.39	-8.8	TT_CYCLE	-4.81	-7.1	TT_TRAIN	-3.88	-9.5	TT_BUS	-5.31	-10.6	TT_PASS	-6.71	-10.2	TT_DRIVE	-6.353	-9.9
Trip Purpose	PURWORK	-0.62	-3.1	PURWORK	1.51	4.4	PURWORK	0.86	5.5				PURWORK	-1.22	-4.6	Reference mode		
	PUREDU	1.51	3.3	PUREDU	2.71	3.1	PUREDU	1.95	4.2	PUREDU	1.83	4.1						
										PURESCO	-2.20	-3.6	PURESCO	-1.75	-3.1			
	PURLEI	0.74	3.4				PURLEI	0.93	4.7				PURLEI	0.68	3.2			
	PURSHOP	0.73	3.8															
	PURPRNL	0.75	2.3															
Time of Day	TIMEAM	0.55	3.4															
													TIMEEVE	0.68	3.0			
Vehicle Ownership	HAVBIKE	0.45	3.2															
	CARS	-1.41	-12.2	CARS	-1.06	-4.5	CARS	-1.29	-11.0	CARS	-1.95	-15.5	CARS	-1.07	-7.8			
Socioeconomic & demographic							YOUNG	0.47	2.0	YOUNG	0.94	3.9	YOUNG	0.46	1.8			
							OLD	-0.87	-3.0				OLD	-0.92	-2.4			
										MALE	-0.41	-3.0	MALE	-1.18	-5.8			
										BRITISH	-0.47	-3.3						
	WORKING	-0.43	-2.4							WORKING	-0.44	-2.2	WORKING	-0.47	-2.2			
	ADULT1	-0.43	-2.6				ADULT1	-0.37	-2.1				ADULT1	-1.08	-3.6			
							ADULT3	0.59	3.7	ADULT3	0.45	2.4	ADULT3	0.49	2.5			
							HAVCHILD	-0.43	-3.1									
							SGRADE	0.10	1.9									
							STUDENT	0.55	1.9									
Land Use										D_POP	0.42	1.8						
	ENTROPY	2.10	2.1							ENTROPY	1.82	1.7	ENTROPY	2.45	1.6			
	OUTERL	-0.64	-4.2	OUTERL	-0.74	-2.3				OUTERL	-0.81	-4.5						
							PTAL	0.15	2.5	PTAL	0.12	1.4						
							ACCTRAIN	0.70	5.3	ACCTRAIN	-0.54	-3.7						
ASC	ASC1	0.87	1.1	ASC2	-2.36	-3.5	ASC3	-1.04	-3.2	ASC4	1.77	1.9	ASC5	-1.00	-0.8			

Latent Variables	Walk	Beta	t	Cycle	Beta	t	Train	Beta	t	Bus	Beta	t	Car Passenger	Beta	t	Car Driver	Beta	t
Environment Attitude	**F_ENV**	**-0.15**	**-0.9**	**F_ENV**	**2.36**	**3.9**	**F_ENV**	**0.36**	**2.4**	**F_ENV**	**-0.07**	**-0.5**	**F_ENV**	**-0.43**	**-2.3**	Reference mode		

Table 5-11 Goodness-of-fit Statistics for Model 3

Model ID	2.3
Latent Variables	Env
# of Observations	2147
Loglikelihood of the Full Model	-16021.2
# of Parameters of the Full Model	105
Loglikelihood of Null1 Model	-16046.7
# of Parameters of the Null1 Model	100
Loglikelihood of Null2 Model	-16925.9
# of Parameters of the Null2 Model	37
Base Null LL	-3387.7
Pseudo R-square	0.267
Pseudo R-square (Adjusted)	0.247

5.3.3 Choice models with multiple latent variables: Model 4

Model 4 introduces six latent factors into the mode choice model simultaneously: *f_Extro*, *f_InCtrl*, *f_Env*, *f_EnvTax*, *f_Conven*, and *f_CarPride*. They are included in the choice utility function in parallel as indicated in Figure 5-2.

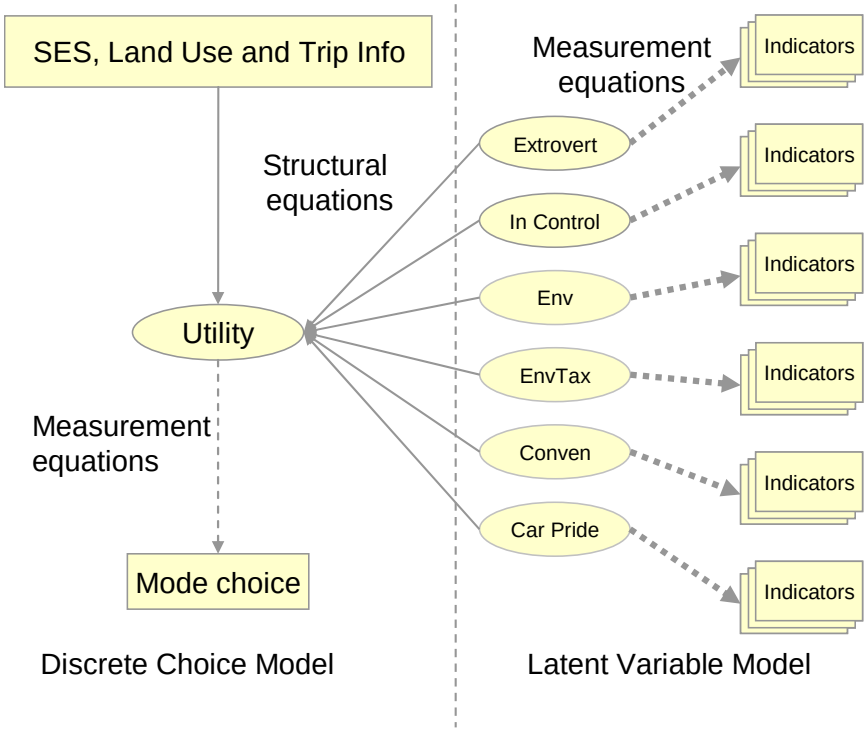


Figure 5-2 Path Diagram of the Choice Model with Multiple Latent Variables in Parallel

Numerical integration becomes increasingly computationally demanding as the number of factors increases: this model requires six dimensions of integration. The standard rectangular (trapezoid) numerical integration or Gauss-Hermite integration methods are

beyond most computers' capacity to calculate within a reasonable time. Instead Monte Carlo integration is used with 500 randomly generated integration points in total. Discussions on Monte Carlo integration can be found in Caflisch (1998) and Weinzierl (2000).

The latent factors are measured by the same sets of indicators as in the MIMIC model in Chapter 2 but the coefficients are estimated simultaneously with the choice model. Table 5-12 gives the measurement equations for the six latent factors. All indicators are significant.

The impacts of the latent factors on the modal choices are summarized in the bottom section of Table 5-13. The two personality factors, in control and extrovert, are significant for the public transportation modes. Both factors contribute positively to the probabilities of using train or bus relative to driving a car. Public transport modes attract people who are extrovert and sociable. There are two plausible expectations of the impact of *f_InCtrl* on mode choice: on one hand, to use public transport effectively often requires travelers to plan things ahead and to control your schedule carefully in order to catch the desired train or bus, therefore *f_InCtrl* increases the probability of using public transit modes relative to car as identified in this model; on the other hand, driving a car provides travelers with a stronger feeling of being in control than being on a bus or train, which suggests *f_InCtrl* should decreases the probability of using public transit. These two interpretations are both plausible but opposite to each other. This seems to suggest two distinct personality traits that both happen to be named as "in control": one emphasizes the capacity to control oneself and one's travels schedule while the other emphasizes the enjoyment of being in control. The finding in this model suggests the indicators chosen in this study refer more to the former trait than the latter. But to fully understand the two aspects of being in control, different sets of indicators may need to be developed for the two aspects.

Table 5-12 Measurement Equations for Latent Factors

Latent Factor: In Control			Latent Factor: Extrovert			Latent Factor: Environ			Latent Factor: EnvTax			Latent Factor: Convenience			Latent Factor: Car Pride		
Indicator	Beta	t	Indicator	Beta	t	Indicator	Beta	t	Indicator	Beta	t	Indicator	Beta	t	Indicator	Beta	t
A33	1.00	999.0	A39	1.00	999.0	A10	1.00	999.0	A02	1.00	999.0	QA1	1.00	999.0	A47	1.00	999.0
A34	0.83	10.0	A42	0.97	10.6	A12	1.04	14.0	A19	1.73	20.6	QA3	2.05	19.6	A53	0.79	16.3
A35	1.66	10.5	A44	1.47	11.1	A13	1.10	14.0	A59	1.24	18.7	QA16	1.52	18.2	A55	1.07	23.6
A38	1.37	7.8	A69	1.36	11.0	A14	0.85	14.7	A66	1.44	23.5	QA21	1.44	18.3	A62	0.95	21.8
A58	1.32	8.4	A70	1.83	12.5	A16	1.33	19.1									
A60	0.84	9.6	A71	1.83	12.4												

Table 5-13 Choice Model with Multiple Latent Factors in Parallel

Observed Variables	Walk	Beta	t	Cycle	Beta	t	Train	Beta	t	Bus	Beta	t	Car Passenger	Beta	t	Car Driver	Beta	t
Travel Time	TT_WALK	-5.30	-13.2	TT_CYCLE	-4.92	-7.1	TT_TRAIN	-3.77	-8.7	TT_BUS	-5.21	-11.3	TT_PASS	-6.58	-9.9	TT_DRIVE	-6.22	-9.7
Trip Purpose	PURWORK	-0.67	-3.2	PURWORK	1.44	4.0	PURWORK	0.80	4.8				PURWORK	-1.24	-4.6	Reference mode		
	PUREDU	1.48	3.3	PUREDU	2.59	3.0	PUREDU	1.82	4.3	PUREDU	1.68	4.1						
										PURESCO	-2.19	-3.6	PURESCO	-1.74	-3.2			
	PURLEI	0.75	3.5				PURLEI	0.89	4.2				PURLEI	0.64	2.9			
	PURSHOP	0.62	3.2															
	PURPRNL	0.69	2.2															
Time of Day	TIMEAM	0.54	3.4															
													TIMEEVE	0.69	3.0			
Car/Bike Ownership	HAVBIKE	0.43	3.1															
	CARS	-1.20	-9.1	CARS	-0.90	-3.5	CARS	-1.01	-7.4	CARS	-1.65	-11.7	CARS	-1.04	-6.7			
Socioeconomic & demographic							YOUNG	0.39	1.5	YOUNG	0.96	4.1	YOUNG	0.52	2.0			
							ELDER	-0.97	-3.1				ELDER	-0.91	-2.4			
										MALE	-0.42	-3.0	MALE	-1.25	-6.2			
										BRITISH	-0.47	-3.3						
	WORKING	-0.43	-2.3							WORKING	-0.52	-2.7	WORKING	-0.42	-1.8			
	ADULT1	-0.36	-2.1				ADULT1	-0.40	-2.1				ADULT1	-1.00	-3.5			
							ADULT3	0.53	3.0	ADULT3	0.38	2.1	ADULT3	0.52	2.5			
							HAVCHILD	-0.44	-2.8									
							SGRADE	0.07	1.3									
							STUDENT	0.54	1.7									
Land Use										D_POP	0.49	2.1						
	ENTROPY	2.10	2.1							ENTROPY	1.93	1.8	ENTROPY	2.11	1.6			
	OUTERL	-0.63	-4.1	OUTERL	-0.85	-2.6				OUTERL	-0.71	-3.8						
							PTAL	0.15	2.3	PTAL	0.11	1.3						
							ACCTRAIN	0.60	4.0	ACCTRAIN	-0.60	-4.0						
ASC	ASC1	0.84	1.0	ASC2	-2.54	-4.7	ASC3	-1.26	-3.4	ASC4	1.45	1.5	ASC5	-0.67	-0.6			

Latent Variables	Walk	Beta	t	Cycle	Beta	t	Train	Beta	t	Bus	Beta	t	Car Passenger	Beta	t	Car Driver	Beta	t
In Control							F_INCTRL	0.73	2.6	F_INCTRL	0.63	2.3				Reference Mode		
Extrovert							F_EXTRO	0.80	3.1	F_EXTRO	0.62	2.2						
Environ				F_ENV	2.65	5.1	F_ENV	0.20	1.2				F_ENV	-0.71	-2.9			
EnvTax													F_TAX	0.69	3.3			
Convenience	F_CONVEN	-1.16	-5.7	F_CONVEN	-1.42	-3.2	F_CONVEN	-2.31	-9.5	F_CONVEN	-1.89	-7.7						
Car Pride	F_CARLOV	-0.44	-3.0				F_CARLOV	-0.29	-1.8	F_CARLOV	-0.36	-2.1						

The perception of car convenience and the sense of car pride decrease the probability of using alternative modes to driving. The perception of car convenience has a particularly strong negative impact on the public transport modes.

The environmental attitude remains a strong positive factor in the use of bicycles. The impacts of "*f_Env*" and "*f_EnvTax*" on the car passenger mode are mixed. On one hand, the environmental attitude decreases the probability of travelling as a car passenger relative to being a car driver. This is counter intuitive since sharing rides in general reduces the environmental impact of car use. Further investigation is required to resolve this contradiction. On the other hand, a positive sign of the factor "*f_EnvTax*" suggests that those who are willing to be taxed in order to improve the environment are more likely to share rides than others.

Two types of changes are notable in the coefficients of the observed variables. The first type includes the changes of the coefficients of CARS, Young, Old, which result from the indirect effect now being captured explicitly via the latent variables in Model 4, rather than being mixed with the direct effects in Model 1.

The second type includes the ASCs for bicycle, train, bus, and car passenger. In the MNL Model the influences of the latent factors are not examined and are simply lumped into the ASCs. By modeling the latent factors explicitly, their impacts are separated from the ASCs and result in the changes of the ASC estimates.

Table 5-14 shows that the model fit improves markedly after introducing the six latent factors with the adjusted pseudo R-square increasing by 9% from 0.241 to 0.269. The likelihood ratio test also confirms that introducing the latent factors significantly improves the data fit of the model. The change in degrees of freedom is 196-181=15. The critical chi-square value at 1% significance level is 30.58. The test statistic is 2*((-85107.8)-(-85219.6)) =223.6, which is greater than the critical value. Therefore we reject the hypothesis that the constrained and unconstrained models are equivalent. The model with the six latent factors provides a significant improvement to the model fit.

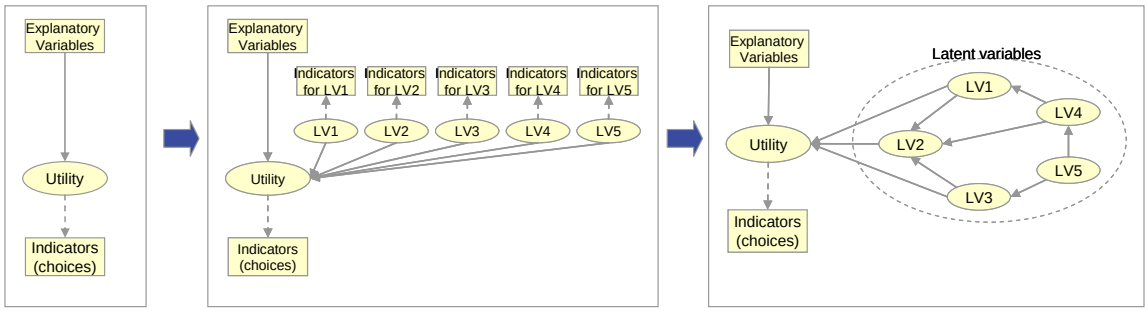
Table 5-14 Goodness-of-fit Statistics for Model 4

Model ID	2.4
# of Observations	2147
Loglikelihood of the Full Model	-85107.8
# of Parameters of the Full Model	196
Loglikelihood of Null1 Model	-85219.6
# of Parameters of the Null1 Model	181
Loglikelihood of Null2 Model	-86098.8
# of Parameters of the Null2 Model	118
Base Null LL	-3388.7
Pseudo R-square	0.292
Pseudo R-square (Adjusted)	0.269

5.3.4 Choice model with multiple latent variables in hierarchical relationship

Model 5 includes the same six latent factors as Model 4 but in a hierarchical structure which preserves the interrelationships among these factors. Figure 5-3 compares the structure of Models 1, 4 and 5. Specifically Figure 5-4 illustrates the full path diagram for Model 5.

The interrelationships among the factors (Table 5-15), the latent factor measurement equations (Table 5-16) and the mode choice model (Table 5-17) are estimated simultaneously. The model is estimated in Mplus 5.1 with the maximum likelihood estimator. Monte Carlo numerical integration method is used with 500 randomly generated integration points in total. The Mplus codes for the models are included in Appendix C-1.



Traditional Choice Model

Latent variable model: latent variables entering the utility function directly and in parallel

Latent variable model: the hierarchical relationships between latent variables being preserved
(Indicators for latent variables are omitted)

Figure 5-3 Comparison between MNL model, Latent Variable Model and Latent Variable Model with Hierarchical Relationship

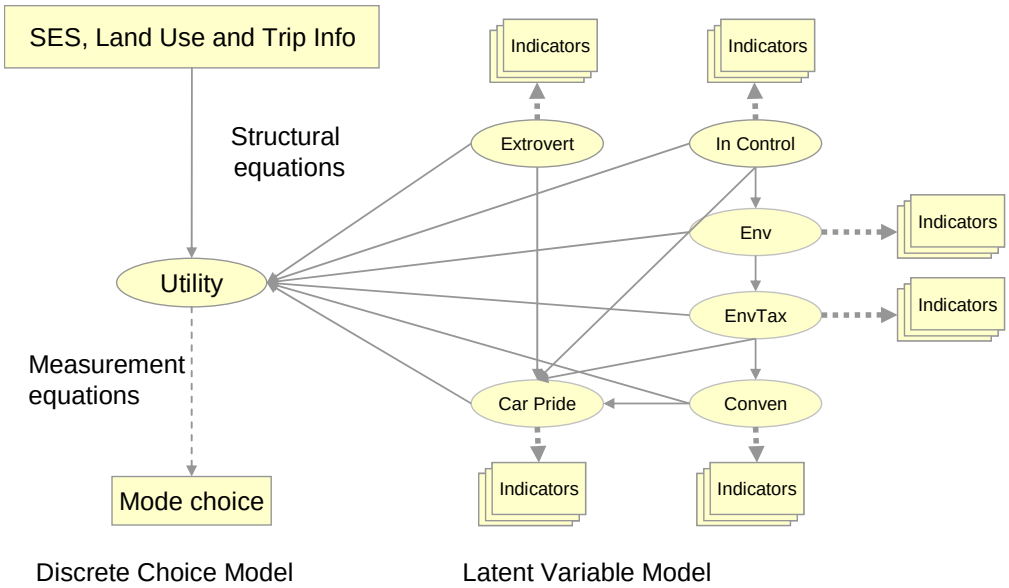


Figure 5-4 Structure of Model 5: Latent Variable Choice Model with Hierarchical Relationship

The estimated coefficients of the path diagram are summarized in Table 5-15. All connections specified in the diagram are significant. Both personality traits *F_InCtrl* and *f_Extro* contribute positively to car pride. Perception of car convenience also adds to car pride, but the willingness to pay taxes for the environment has a negative impact on car pride.

Table 5-15 Coefficients of the Path Analysis among Latent Factors

Dependent Var	Indep Var	Beta	t
F_ENV	F_INCTRL	0.13	4.2
F_EnvTax	F_ENV	0.49	19.8
F_CarPride	F_INCTRL	0.24	7.7
F_CarPride	F_EXTRO	0.19	6.4
F_CarPride	F_CONVEN	0.21	7.2
F_CarPride	F_EnvTax	-0.35	-12.8
F_CONVEN	F_EnvTax	-0.35	-14.2

As for the choice model, the sets of coefficients in models 4 and 5 show only minor differences: all signs are consistent and their magnitudes are within 5% of each other. While there are some adjustments to the coefficients in the measurement equations, they are small. The overall model fit improves significantly from the base MNL model but only slightly from Model 4 with adjusted pseudo R-square increasing from 0.269 to 0.270 as shown in Table 5-18.

Table 5-16 Measurement Equations for Latent Factors

Latent Factor: In Control			Latent Factor: Extrovert			Latent Factor: Environ			Latent Factor: EnvTax			Latent Factor: Convenience			Latent Factor: Car Pride		
Indicator	Beta	t	Indicator	Beta	t	Indicator	Beta	t	Indicator	Beta	t	Indicator	Beta	t	Indicator	Beta	t
A33	1.00	999.0	A39	1.00	999.0	A10	1.00	999.0	A02	1.00	999.0	QA1	1.00	999.0	A47	1.00	999.0
A34	0.83	10.0	A42	0.99	10.8	A12	1.05	13.8	A19	1.79	20.2	QA3	2.09	19.3	A53	0.79	16.3
A35	1.68	10.7	A44	1.49	11.4	A13	1.12	13.8	A59	1.28	18.4	QA16	1.56	18.0	A55	1.08	23.7
A38	1.37	7.9	A69	1.36	11.3	A14	0.86	14.5	A66	1.48	23.0	QA21	1.48	18.1	A62	0.95	21.8
A58	1.34	8.5	A70	1.83	12.9	A16	1.39	19.0									
A60	0.84	9.6	A71	1.83	12.8												

Table 5-17 Choice Model with Multiple Latent Factors and Hierarchical Relationship

Observed Variables	Walk	Beta	t	Cycle	Beta	t	Train	Beta	t	Bus	Beta	t	Car Passenger	Beta	t	Car Driver	Beta	t
Travel Time	TT_WALK	-5.30	-13.2	TT_CYCLE	-4.92	-7.1	TT_TRAIN	-3.77	-8.7	TT_BUS	-5.21	-11.3	TT_PASS	-6.58	-9.9	TT_DRIVE	-6.22	-9.7
Trip Purpose	PURWORK	-0.67	-3.2	PURWORK	1.44	4.0	PURWORK	0.80	4.8				PURWORK	-1.24	-4.6	Reference mode		
	PUREDU	1.48	3.3	PUREDU	2.59	3.0	PUREDU	1.82	4.3	PUREDU	1.68	4.1						
										PURESCO	-2.19	-3.6	PURESCO	-1.75	-3.2			
	PURLEI	0.75	3.5				PURLEI	0.89	4.2				PURLEI	0.64	2.9			
	PURSHOP	0.62	3.2															
	PURPRNL	0.69	2.2															
Time of Day	TIMEAM	0.54	3.4															
													TIMEEVE	0.69	3.0			
Vehicle Ownership	HAVBIKE	0.43	3.1															
	CARS	-1.20	-9.1	CARS	-0.90	-3.5	CARS	-1.01	-7.4	CARS	-1.65	-11.7	CARS	-1.04	-6.7			
Socioeconomic & demographic							YOUNG	0.39	1.5	YOUNG	0.96	4.1	YOUNG	0.52	2.0			
							ELDER	-0.97	-3.1				ELDER	-0.91	-2.4			
										MALE	-0.42	-3.0	MALE	-1.25	-6.2			
										BRITISH	-0.47	-3.3						
	WORKING	-0.43	-2.3							WORKING	-0.52	-2.6	WORKING	-0.42	-1.8			
	ADULT1	-0.36	-2.1				ADULT1	-0.40	-2.1				ADULT1	-0.99	-3.5			
							ADULT3	0.53	3.0	ADULT3	0.38	2.1	ADULT3	0.53	2.5			
							HAVCHILD	-0.44	-2.8									
							SGRADE	0.07	1.3									
							STUDENT	0.54	1.7									
Land Use										D_POP	0.49	2.1						
	ENTROPY	2.11	2.1							ENTROPY	1.93	1.8	ENTROPY	2.11	1.6			
	OUTERL	-0.63	-4.1	OUTERL	-0.85	-2.6				OUTERL	-0.71	-3.8						
							PTAL	0.15	2.2	PTAL	0.11	1.3						
							ACCTRAIN	0.60	4.0	ACCTRAIN	-0.60	-4.0						
ASC	ASC1	0.83	1.0	ASC2	-2.54	-4.7	ASC3	-1.26	-3.5	ASC4	1.44	1.5	ASC5	-0.68	-0.6			

Latent Variables	Walk	Beta	t	Cycle	Beta	t	Train	Beta	t	Bus	Beta	t	Car Passenger	Beta	t	Car Driver	Beta	t
In Control							F_INCTRL	0.74	2.7	F_INCTRL	0.63	2.3				Reference Mode		
Extrovert							F_EXTRO	0.84	3.2	F_EXTRO	0.65	2.3						
Environ				F_ENV	2.71	5.0	F_ENV	0.20	1.1				F_ENV	-0.71	-2.8			
EnvTax													F_TAX	0.71	3.3			
Convenience	F_CONVEN	-1.18	-5.6	F_CONVEN	-1.40	-3.1	F_CONVEN	-2.37	-9.5	F_CONVEN	-1.93	-7.7						
Car Pride	F_CARLOV	-0.44	-3.0				F_CARLOV	-0.29	-1.8	F_CARLOV	-0.36	-2.1						

Table 5-18 Goodness of Fit Statistics for Model 5

Model ID	2.5
# of Observations	2147
Loglikelihood of the Full Model	-85114.5
# of Parameters of the Full Model	189
Loglikelihood of Null1 Model	-85226.7
# of Parameters of the Null1 Model	174
Loglikelihood of Null2 Model	-86105.9
# of Parameters of the Null2 Model	111
Base Null LL	-3388.7
Pseudo R-square	0.293
Pseudo R-square (Adjusted)	0.270

Table 5-19 Summary of Goodness of Fit for Models 1 through 5

Types	Models	Adjusted Pseudo R-Square	% change over Model 1
MNL Model	Model 1 Baseline MNL Model	0.241	n.a.
Latent Variable Models	Model 2 Choice Model with the Car Pride	0.245	1.7%
	Model 3 Choice Model with the Environmental Attitude	0.247	2.5%
	Model 4 Choice Model with Multiple Latent Factors	0.269	11.6%
	Model 5 Choice Model with Multiple Latent Factors and Hierarchical Relationships	0.270	12.0%

Table 5-19 summarizes the overall model fits for the five choice models. The model fit progressively improves with more latent variables included. The introduction of latent factors enriches the aspects of traveler preferences that can be captured by the choice models and improves the explanatory power of the choice model.

5.4 Modeling Unobserved Heterogeneity in Traveler Preferences with Latent Classes Models

Traveler preference heterogeneity is well recognized by transportation planners. Some people value travel time savings more than others; some pay more attention to the environmental consequences of transport options; some are more sensitive to social image; some prefer more convenient options than simply faster options, etc. Interviews with several TfL staffs suggest that one goal of Transport for London is to provide the best travel option for each individual's individual trips which conveys the importance of

understanding heterogeneity in traveler preferences in order to serve the diverse needs of each individual.

Observed heterogeneity can be incorporated into mode choice models by introducing individual socio-economic characteristics and interacting them with level-of-service attributes or segmenting the market through multiple-group analysis.

In addition to the observed heterogeneity, there are also heterogeneities due to unobserved individual attributes, which are often ignored in traditional transportation models. Two techniques have been advanced to account for unobserved heterogeneity in mode choice models: the latent class choice model (finite mixture model) and the random coefficients mixed logit model. A recent study by Greene and Hensher (2003) compared the latent class choice model with the mixed logit model in the case of driver's road type choice in New Zealand and concluded that each model has its virtues and limitations.

In this research, the latent class choice model is used to capture of the unobserved heterogeneity because of two advantages it has over the mixed logit model: 1) unlike the mixed logit model, the latent class choice model does not require analysts to make specific assumptions about the distributions of parameters across individuals; and 2) the latent class choice model explicitly links preference heterogeneity to socioeconomic and demographic characteristics

Latent class analysis was introduced by Lazarsfeld and Henry (1968) as a way of formulating latent attitudinal variables based on dichotomous survey items. Later latent class analysis was introduced to choice models (Gopinath 1995, Bhat 1997, Swait 1994). The guiding theme remains that the overall population is comprised of a mixture of heterogeneous subgroups each of which consist of similar individuals. In the marketing research context, the latent classes are typically interpreted as market segments (Dillon and Kumar 1994; Wedel and Kamakura 1998).

This section employs latent class choice model techniques to examine the unobserved heterogeneity in people's taste in observed level of service variables, but also extends the technique to examine the unobserved heterogeneity in people's taste in latent variables. This study also explores the possibility of using latent variables in the class membership model, as well as the SES variables which are usually used to define class membership.

Variables play different roles in the latent class model: some could be allowed to differ across classes while others are constrained to be the same, some could be used to define the classes by entering the class membership model, and others might serve as covariates in the structural equations of the latent variables. While there are many ways in which latent class models can be constructed, here four models are presented to test the four specific hypotheses listed in Table 5-20.

Table 5-20 Hypotheses tested through latent class and latent variable models

Model ID	Model Type	Hypotheses to be Tested
Model 6	Typical Latent Class Model	People's sensitivity to travel time may differ across latent classes
Model 7	Latent Class Model with Latent Variables	People's sensitivity to the perception of car convenience may differ across latent classes
Model 8	Latent Class Model with Latent Variables	People who are extrovert may be more sensitive to travel time
Model 9	Latent Class Model with Latent Variables	People with a stronger sense of car pride may pay more attention to the perception of car convenience

Model 6 sets up a typical latent class choice model, in which both the variables whose coefficients differ across classes and the variables that define class membership are observed. Specifically the latent class model examines the heterogeneity in travelers' sensitivities to travel time and defines the class membership using travelers' socio-economic status. Models 7, 8 and 9 present three variations of models which combine latent variable and latent class. Model 7 tests the hypothesis that people's sensitivities to the perception of convenience may differ across latent classes; Model 8 introduces the latent factor being extrovert to the latent class membership model and

tests the hypothesis that being extrovert may influence travelers' sensitivities to travel time; and Model 9 incorporates both ways of combining the latent variables and latent classes and tests the hypothesis that people with a stronger sense of car pride may pay more attention to the level of convenience of travel options.

5.4.1 Heterogeneity in the Sensitivity to Travel Time

The structure of model 6 is illustrated in Figure 5-5. Both the SES variables and travel time "TT" enter the utility function. Categorical latent variable c indicates the latent class membership. Following the graphing convention in latent class SEM models, the dashed arrow from c to the arrow from "TT" to "Utility" indicates that the coefficient of "TT" in the utility function varies across the classes that the variable c represents. The latent class membership model is an MNL regression of *c* on the SES variables.

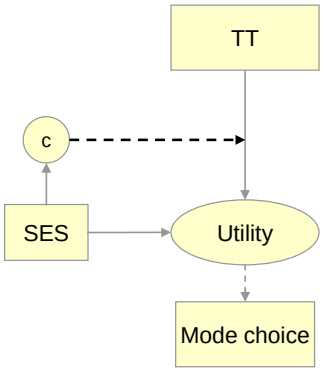


Figure 5-5 Path Diagram of Latent Class Model 6

The model is estimated in Mplus 5.1. The finite mixture models are known to be prone to multiple local maxima (McLachlan and Peel, 1998). Since the expectation-maximization (EM) algorithm used by Mplus 5.1 is a local greedy algorithm, the estimation results will depend on good initialization. Multiple random starts are often employed to ensure finding the global maximum. If the best (highest) loglikelihood value is not replicated in at least two final stage solutions and preferably more, it is possible that a local solution has been reached. Muthen and Muthen (2007) recommend an increasingly more thorough investigation by gradually increasing the number of random starts and iterations. In Model 5, 50 random sets of starting values are used at

the initial stage, followed by 4 final stage optimizations. All four final stage optimizations return the same loglikelihood values indicating a very high chance that the global maximum has indeed been found.

Table 5-21 and Table 5-22 report the estimation results with two latent classes, the former listing the coefficients that are the same across classes and the latter listing the coefficients of the travel time variable[6], which differ across classes: the magnitudes of its coefficients in class 2 are much larger than those in class 1, indicating a higher sensitivity to travel time of the people in class 2. Comparing the magnitudes of the travel time coefficients to those of the other variables in class 2, the impact of travel time dominates all other variables in the modal probability given that the utility function appears in the exponent in the MNL probability formula. In effect, travel time becomes the sole factor determining mode choice for people in class 2. For people in class 1, the travel time is still important but its influence is considered together with other significant variables in the mode choice decision.

Table 5-23 records the estimation results for the binary logistic regression model of the class membership with the SES variables as independent variables and Table 5-24 gives the class counts. Class 2 is chosen as the reference class. The dummy variable of the work trip is significant at the 5% level. Its negative coefficient suggests that for commuting trips, people are more likely to belong to class 2, paying attention only to travel time in their decision making. People who are employed have a similar tendency to belong to class 2. Being old and having children have positive impacts on the probability of belonging to class 1. This is intuitive because these two groups tend to consider more factors when making mode choice than simply the shortest travel time.

[6] To facilitate estimation, the coefficients of the travel time in class 1 are constrained to be same across modes.

Table 5-21Coefficients that are common across classes

Observed Variables	Walk	Beta	t	Cycle	Beta	t	Train	Beta	t	Bus	Beta	t	Car Passenger	Beta	t	Car Driver
Trip Purpose	PURWORK	-0.51	-2.0	PURWORK	1.43	3.7	PURWORK	0.37	1.4				PURWORK	-1.44	-4.4	Reference Case
	PUREDU	1.96	4.1	PUREDU	2.66	3.1	PUREDU	2.19	5.3	PUREDU	2.05	5.3				
										PURESCO	-2.18	-3.5	PURESCO	-1.69	-3.2	
	PURLEI	0.65	2.7				PURLEI	0.95	3.6				PURLEI	0.72	3.2	
	PURSHOP	0.59	2.8													
	PURPRNL	0.59	1.8													
Time of Day	TIMEAM	0.61	3.4													
													TIMEEVE	0.67	2.8	
Vehicle Ownership	HAVBIKE	0.48	3.2													
	CARS	-1.55	###	CARS	-1.32	-4.7	CARS	-1.46	-8.5	CARS	-2.07	-13.1	CARS	-1.07	-6.0	
Socioeconomic & demographic							YOUNG	0.75	2.5	YOUNG	1.07	4.7	YOUNG	0.63	2.2	
							OLD	-0.31	-0.7				OLD	-0.86	-2.1	
										MALE	-0.35	-2.4	MALE	-1.16	-5.6	
										BRITISH	-0.45	-3.1				
	WORKING	-0.38	-1.9							WORKING	-0.38	-1.8	WORKING	-0.53	-2.1	
	ADULT1	-0.36	-1.9				ADULT1	-0.44	-1.8				ADULT1	-1.02	-3.5	
							ADULT3	0.67	2.7	ADULT3	0.45	2.6	ADULT3	0.54	2.4	
							HAVCHILD	-0.40	-1.7							
							SGRADE	0.11	1.4							
							STUDENT	0.64	1.6							
Land Use										D_POP	0.30	1.2				
	ENTROPY	2.89	2.5							ENTROPY	2.05	1.8	ENTROPY	2.63	2.1	
	OUTERL	-0.82	-4.7	OUTERL	-1.02	-2.8				OUTERL	-0.93	-4.5				
							PTAL	0.19	2.5	PTAL	0.15	1.8				
							ACCTRAIN	0.90	4.5	ACCTRAIN	-0.52	-3.4				

Table 5-22 Coefficients that differ across classes

Latent Class 1			Latent Class 2		
Mode	Beta	t	Mode	Beta	t
TT_WALK	-2.33	-7.2	TT_WALK	-41.0	999.0
TT_CYCLE	-2.33	-7.2	TT_CYCLE	-10.4	-3.5
TT_TRAIN	-2.33	-7.2	TT_TRAIN	-12.7	-8.4
TT_BUS	-2.33	-7.2	TT_BUS	-18.4	-10.3
TT_PASS	-2.33	-7.2	TT_PASS	-22.3	-8.5
TT_DRIVE	-2.33	-7.2	TT_DRIVE	21.2	8.3

Table 5-23 Binary logistic class membership model

Indep. Var	Beta	t
OLD	0.864	1.6
PURWORK	-0.784	-3.3
WORKING	-0.555	-1.7
HAVCHILD	0.399	1.8
Intercept	0.654	2.0

Table 5-24 Class membership counts

Classes	#obs	%
1	1165	54.3%
2	982	45.7%
Total	2147	100%

5.4.2 Heterogeneity in the sensitivity to the perception of convenience

As illustrated in Figure 5-6, typical latent class models allow the coefficients of observed variables to differ across classes, while Model 7 implements a latent class model in which the impact of a latent variable can differ across classes. The dashed arrow in the right panel from c to the arrow from latent variables to utility indicates that the coefficients of the latent variables in the utility function are influenced by the class membership c. Specifically Model 7 tests the hypothesis that the importance people attach to the perception of convenience may vary across different groups of people.

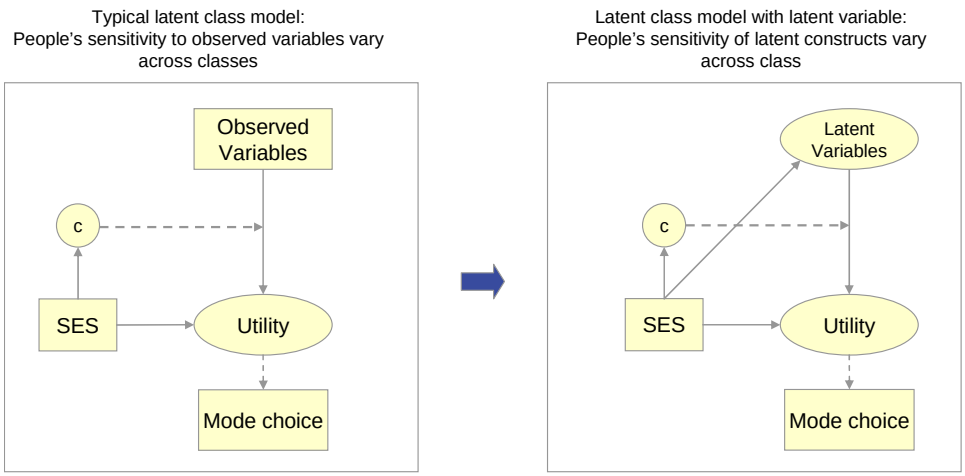


Figure 5-6 Comparison of Model 7 with a typical latent class model

Multiple random starts are again used in the estimation of model 7 in Mplus. The author tried to estimate models with two, three or four latent classes. But the best loglikelihood value could not be replicated in the models with three and four latent classes, even after increasing the random starts to 200. Further investigation is needed to understand this. The best loglikelihood value was replicated in the model with two latent classes. The results of the model with two latent classes are reported in Tables 5-25 through 5-29.

The latent variable "perception of convenience" is measured by the four indicators in Table 5-29. The coefficients of the latent variable perception of convenience in the utility function are allowed to differ across classes. In both classes, the coefficients are negative for walking, cycling, and public transport because the car is usually perceived as more convenient than these other modes and the probability of using alternative modes decreases accordingly. But the magnitudes of the coefficients for class 2 are larger than those for class 1, indicating that people in class 2 are more sensitive to convenience than people in class 1. The binary logistic class membership model reported in Tables 5- 27 and 5-28 reveals that people who have children or who own cars are more likely to be in class 2, whose members value convenience more. The two classes roughly split the population in half. Latent class 2 is chosen as the reference case.

The differences between the coefficients for class 2 and class 1 vary by mode: for train, the differences between the classes are negligible, indicating that the impacts of the convenience factor on the probability of choosing train are homogenous across the population. But for walking, cycling and bus, there is a sharp difference between how people respond to the perception of convenience: the coefficients for class 2 are more than three times as large as for class 1. For people in class 2, the perception of convenience plays a much stronger role in their preference of car over walk, bicycle or bus.

Table 5-25 Coefficients that are the same across classes

Indep.	Walk		Cycle		Train		Bus		Car Passenger		Car Driver	
Variables	Estimate	t	Estimate	t	Estimate	t	Estimate	t	Estimate	t	Estimate	t
TT_WALK	-5.37	-13.5	-4.66	-7.1	-3.75	-8.9	-5.24	-11.6	-6.54	-10.1	-6.19	-9.9
PURWORK	-0.62	-3.0	1.20	3.6	0.76	4.7			-1.17	-4.3		
PURSHOP	0.68	3.6										
PUREDU	1.47	3.3	2.22	2.7	1.77	4.2	1.69	4.0				
PURLEI	0.76	3.5			0.93	4.4			0.64	2.9		
PURPRNL	0.77	2.4										
PURESCO							-2.20	-3.5	-1.82	-3.4		
TIMEAM	0.58	3.6										
TIMEEVE									0.71	3.1		
BRITISH							-0.49	-3.4				
OLD					-1.08	-3.5			-0.98	-2.6		
YOUNG					0.48	1.9	1.04	4.5	0.57	2.2		
MALE							-0.38	-2.7	-1.21	-6.1		
SGRADE					0.10	1.8					Base	
STUDENT					0.47	1.5						
WORKING	-0.45	-2.4					-0.48	-2.4	-0.43	-1.9		
HAVBIKE	0.42	3.0										
CARS	-1.29	-8.8	-1.04	-3.8	-0.91	-6.5	-1.71	-10.2	-1.07	-7.0		
ADULT1	-0.35	-2.0			-0.40	-2.2			-0.98	-3.5		
ADULT3					0.52	2.9	0.37	2.0	0.52	2.5		
HAVCHILD					-0.46	-3.0						
OUTERL	-0.61	-4.0	-0.92	-2.9			-0.74	-3.9				
ENTROPY	2.20	2.1					1.83	1.7	2.27	1.7		
PTAL					0.16	2.6	0.11	1.3				
D_POP							0.44	1.9				
ACCTRAIN					0.63	4.3	-0.61	-4.0				
ASC	0.38	0.4	-2.27	-4.1	-2.46	-6.3	0.61	0.6	-0.78	-0.7		

Table 5-26 Coefficients that differ across classes

Modes		Class 1		Class 2	
		Beta	t	Beta	t
MODE#1	Walk	-0.88	-4.0	-3.30	-3.5
MODE#2	Cycle	-1.24	-2.8	-2.41	-1.1
MODE#3	Train	-2.20	-9.4	-2.24	-2.1
MODE#4	Bus	-1.79	-6.7	-5.44	-3.6
MODE#5	Car Pass	Insignificant (excluded in the simplied model)			
MODE#6	Car Driver	Reference case			

Table 5-27 Class membership model

Class Membership Model

Indep Vars	Beta	t
CARS	-1.637	-13.8
HAVBIKE	0.271	2.1
WORKING	0.356	1.9
STUDENT	0.771	2.6
ADULT3	0.425	2.8
HAVCHILD	-0.268	-2.1
Intercepts	1.491	7.3

Table 5-28 Class Membership Counts

Classes	#obs	%
Class 1	1143	53%
Class 2	1004	47%
Total	2147	100%

Table 5-29 Measurement equations for the factor convenience

Indicators	Beta	t
QA1	1.00	999.0
QA3	2.29	17.9
QA16	1.49	17.1
QA21	1.41	17.2

In terms of the hypothesis underlying Model 7, people's sensitivities to the perception of convenience do indeed differ significantly across classes, particularly with respect to walk, bicycle and bus. People who have children or who own cars value convenience more than others.

5.4.3 Class membership defined by latent variables

Both Models 6 and 8 examine the heterogeneity in people's sensitivity to travel time but Model 8 is different in its definition of class membership. Model 6 defines the membership model by observed SES variables while Model 8 defines it by the latent variable "extrovert" with a hypothesis that people who are extrovert may be more sensitive to travel time than others. The model structure is shown in Figure 5-7

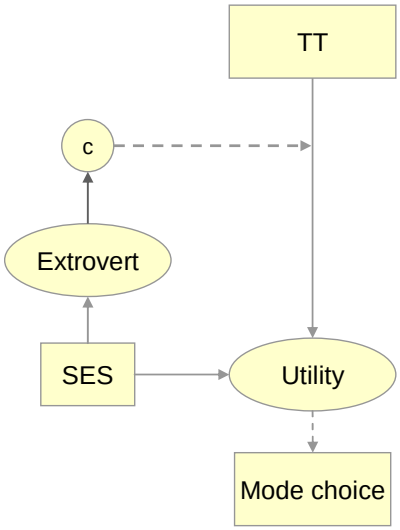


Figure 5-7 Schematic Diagram of Latent Class Model 8

Table 5-30 Coefficients that differ across classes in Model 8

Latent Class 1			Latent Class 2		
Mode	**Beta**	**t**	**Mode**	**Beta**	**t**
TT_WALK	-2.76	-7.1	TT_WALK	-17.03	-9.3
TT_CYCLE	-2.76	-7.1	TT_CYCLE	-8.89	-8.2
TT_TRAIN	-2.76	-7.1	TT_TRAIN	-7.58	-9.4
TT_BUS	-2.76	-7.1	TT_BUS	-11.39	-11.3
TT_PASS	-2.76	-7.1	TT_PASS	-13.18	-9.5
TT_DRIVE	-2.76	-7.1	TT_DRIVE	-12.55	-9.8

The two classes remain as in Model 6 consisting of one more time-sensitive group and one less time-sensitive group. As shown in Table 5-30, the magnitude of the coefficients of the travel time variables for class 2 suggests that the time sensitive group effectively only consider travel time in the mode choice decisions. The negative sign of the factor *f_Extro* in the class membership model (Table 5-31) suggests that people who are extrovert are more likely to belong to class 2, supporting the hypothesis.

Table 5-31 Class Membership Model in Model 8

Indep Vars	Beta	t
F_EXTRO	-0.648	-2.0
Intercept	-0.815	-4.6

5.4.4 Combining latent class model and latent variable models

Models 7 and 8 presented two ways in which latent variable model can be combined with the latent class model. Model 9 includes both ways of combining the latent variables and latent class and tests the hypothesis that people with a stronger sense of car pride may pay more attention to the perception of convenience of travel options.

As indicated in Figures 5-8 and 5-9, two latent variables “Car Pride” and “Convenience” are included in Model 9 but they play two distinct roles in the model. The core of the model remains an MNL choice model (middle section of Figure 5-8), enhanced by a latent variable model to capture “perception of convenience” (right section), and a latent class model to identify groups with different sensitivities to “convenience”, whose membership is defined by SES variables as well as another latent variable “Car Pride” (left section).

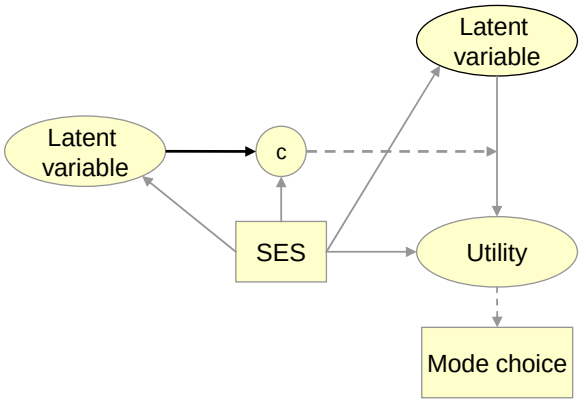


Figure 5-8 Schematic Diagram for Model 9

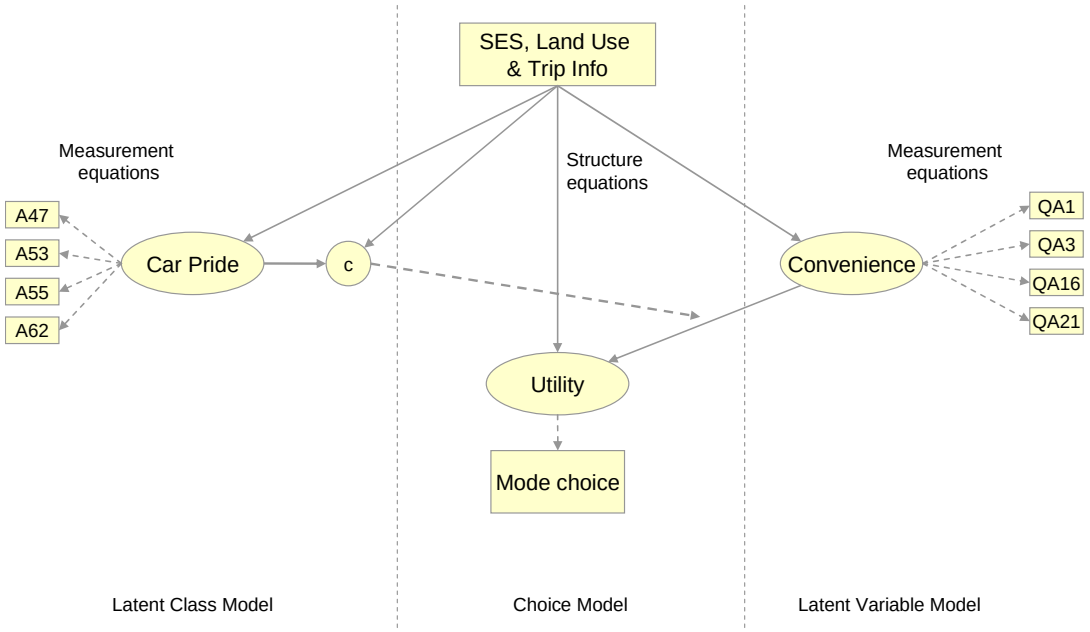


Figure 5-9 Full Path Diagram for Model 9

A thorough search for the global maximum was carried out using 200 random sets of starting values in the initial optimization stage and 10 in the final optimization stage. Five local maxima in the final stage replicate the same highest value (-23952.03), indicating a high chance that the global maximum has indeed been found.

Table 5-32 shows the coefficients that differ across classes: similar to Model 7, there exist two classes of people with different levels of sensitivity to convenience. The enhancement in Model 9 comes in the class membership model, which includes the latent factor "Car Pride" in addition to the SES variables, shown in Table 5-33. The class membership model itself is a latent variable choice model. The negative sign of "*f_CarPride*" indicates that people with a stronger sense of car pride are more likely to belong to Class 2, as are people who have children or own cars. Table 5-33 shows that people in class 2 have much larger coefficients for the convenience factor for walk, bicycle and bus than people in class 1, but a slightly smaller coefficient for train. It seems that people in the two classes have different emphases on convenience of different modes but overall, people in class 2 value convenience more than people in class 1. The

results in Tables 5-33 and 5-34 support the hypothesis that people with a stronger sense of car pride pay more attention to the perception of convenience of alternative modes.

Table 5-32 Coefficients that differ across classes in Model 9

Coefficients of f_Convenience by Class and Mode				
	Class1		Class 2	
Modes	Beta	t	Beta	t
Walk	-0.858	-3.8	-3.760	-3.7
Cycle	-1.172	-2.5	-3.712	-1.5
Train	-2.232	-9.3	-1.898	-1.8
Bus	-1.765	-6.6	-5.657	-3.7
Car Passenger	Insignificant			
Car Driver	Reference case			

Table 5-33 Class Membership Model in Model 9

Indep Vars	Beta	t
CARS	-1.52	-13.3
HAVBIKE	0.22	1.7
WORKING	0.36	1.9
STUDENT	0.78	2.6
ADULT3	0.42	2.8
HAVCHILD	-0.34	-2.6
Intercepts	1.45	7.0
f_CarPride	-0.42	-2.7

5.5 Summary

This chapter tested whether the proposed structure of traveler preferences can be applied in the context of discrete mode choice. The nine models presented in this chapter illustrate:

1) the structure that includes personality traits, environmental attitudes, car pride and perceptions of convenience and comfort can be applied to travel mode choice thanks to the recent methodological innovations such as latent variable and latent class choice models;

2) the introduction of the six latent factors into the model enriches the definition of traveler preferences and improves the explanatory power of the model; and the

hierarchical relationship among the factors can be simultaneously estimated with the factor measurement equations and the mode choice models; and

3) unobserved heterogeneities exist not only for preferences with respect to the observed variables such as travel time, but also for the latent factors such as perception of convenience; and both observed SES variables and the latent attitudinal factors can be used to define class membership.

Chapter 6. Traveler Preference and Car Ownership

Chapters 4 and 5 focused on traveler preferences as they affect car usage given the car ownership level. This chapter examines the car ownership decision itself.

In the past half century, the number of vehicles in Great Britain has increased tenfold from 2.6 million in 1951 to 27 million in 2001 (UK Department for Transport 2003). Collective household car ownership decisions largely define the nature and scope of urban transportation problems and the associated consequences on the climate, energy, sustainability, and ecological systems. Cars can be either the maker or the breaker of cities. (Clark 1957)

Conversely growing discussion of global warming and environmental sustainability, and changes in social attitudes toward cars may be influencing car ownership decisions.

This chapter incorporates latent factors of traveler preferences including personality traits, environmental attitudes, car pride and perceptions of convenience and comfort into car ownership models. Because of the potential mutual dependencies between car ownership and traveler preferences, the model tests the specification in which car ownership decisions feed back to the structural equations for the latent factors to capture the feedback from car ownership to traveler preferences.

This chapter also examines the heterogeneity among the population in their response to these latent factors by including latent classes in the choice model.

Three sets of models of car ownership are presented as shown in Table 6-1.

Table 6-1 Models of Car Ownership

Types	Models
MNL Model	Model 1 MNL Model with SES Variables
	Model 2 MNL Model with SES, Land Use and PT Access variables (Baseline)
Latent Variable Choice Models	Model 3 Choice Model with Multiple Latent Factors
Latent Class Choice Models (with latent variables)	Model 4 Latent Class Model Testing Heterogeneity in the Sensitivity to Car Pride
	Model 5 Latent Class Model Testing Heterogeneity in the Sensitivity to the Perception of Convenience

Section 6.1 reviews the car ownership literature. Section 6.2 describes current car ownership levels in London and the trend over the past two decades. Section 6.3 presents two MNL models to examine the impact of SES, land use and PT access on car ownership and these models serve as the baseline for later comparison. Section 6.4 presents a latent variable choice model that incorporates the latent factors of traveler preferences into the car ownership models. Section 6.5 presents three latent class choice models to examine the heterogeneity of travel preferences on car ownership. Section 6.6 concludes.

6.1 Car Ownership Literature

Because of the importance of car ownership to transportation planning, it has been a heavily researched area. Bunch (2000) and De Jong et al (2004) offered two good summaries of literature on car ownership. Recent studies include: Matas and Raymond (2008) analyzed factors determining car ownership growth in Spain over the past two decades, Giuliano and Dargay (2006) compared car ownership in the US and Great Britain and the relationship between car ownership and daily travel, and Whelan (2007) developed a car ownership model and applied it to generate forecasts in Britain to the year 2031.

The decision about how many cars a household owns can be modeled as a discrete choice. One methodological question is whether the car ownership decision follows an ordered response or an unordered response mechanism.

Kitamura and Bunch (1990), Pendyala et al (1995), Dargay and Hanly (2004) and Giuliano and Gargay (2006) have modeled the car ownership decision as an ordered process so that the dependent variable has a natural interpretation as an increasing integer and the values assigned to each outcome are not arbitrary.

Mannering and Winston (1985), Train (1986) and Hensher (1992), in contrast, have modeled car ownership based on an unordered-response mechanism using multinomial specifications.

Bath and Pulugurta (1998) compared these two model specifications using several data sets and concluded that the multinomial logit model is preferred in terms of the forecasting performance and measures of fit. Matas and Raymond (2008) also compared these two model specifications but concluded instead that the multinomial logit model and the ordered probit model are almost indistinguishable in terms of their forecasting performance.

This chapter uses an MNL model specification and focuses on two different modeling aspects:

1) To incorporate psychological factors in the car ownership model

Most econometric models of car ownership have focused on socio-economic characteristics, the cost of buying and using cars, and land use and transportation systems. However these models do not usually consider consumers' attitudes, personality and perceptions as factors that may affect car ownership decisions. A few related studies include Choo and Mokhtarian (2004) who introduced latent attitudinal and lifestyle factors to explain the vehicle type choice; Ibrahim (2003) who analyzed the relationship between car owners and non-car owners' perceptions of the different transport modes in Singapore; and Allen and Ng (1999) who studied the influence of the human values on product choice using car type choice as an example.

2) To examine the causal relationship between car ownership and traveler preferences such as environmental attitudes and car pride

Kitamura (1989) examined the causal structure between car ownership, car trip frequency, and transit trip frequency. See section 4.2 for the discussion of the mutual dependencies between travel behavior and traveler preferences.

6.2 Car Ownership in London and Great Britain

Car ownership in London is different from the rest of Great Britain both in term of current levels and in terms of the growth trend, which makes it interesting to examine the car ownership decision in London.

Car ownership in London is much lower than in the rest of Great Britain: about 40% of London households do not have access to a car, compared with less than a quarter in the rest of Great Britain. Roughly the same proportion of households own one car. The main difference occurs in households owning two or more cars: over a third of households in the rest of Great Britain own two or more cars, twice the proportion in London (see Table 6-2).

Table 6-2 Car Ownership in London and the Rest of Great Britain

Car Ownership	No car	One Car	Two or More cars
London	40%	44%	16%
Rest of Great Britain	23%	43%	34%

Source: UK Department for Transportation, National Travel Survey, 2007

Large households tend to have more cars than small ones (Table 6-3). This trend is particularly strong for households owning two or more cars. Car ownership increases with household income (Figure 6-1). There are substantial differences between the income bands: at the lower income bands, income influences the decision to own a car or not; whereas in the upper income bands, the decision is typically between owning one or more cars.

Table 6-3 Car Ownership in London by Household Size

Number of cars	Number of people in household				
	One	Two	Three	Four or more	All households
No car	63%	34%	30%	31%	40%
One car	36%	49%	48%	44%	44%
Two or more cars	1%	17%	21%	36%	16%
Total	100%	100%	100%	100%	100%

Source: UK Department for Transportation, National Travel Survey, 2007

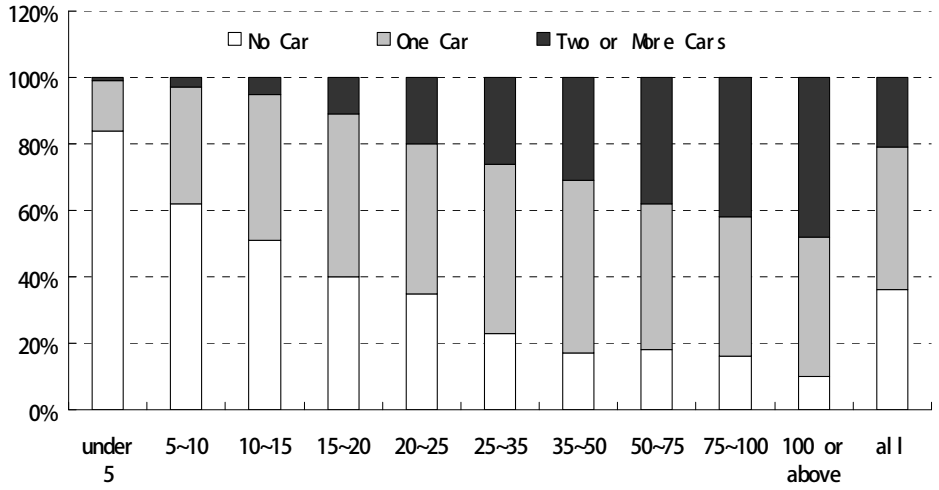


Figure 6-1 Car ownership by household income band (in thousand pounds)
Source: London Travel Demand Survey (LTDS) 2007~2008.

Figure 6-2 shows that car ownership in London has been largely stable since the mid-1980s and slightly declining in recent years, in contrast to the rest of Great Britain, where the cars owned per household has risen steadily. Although the proportions fluctuate from year to year, recent years show a decline in car ownership in London particularly in the proportion of households with more than one car, which has dropped from 21% in 2001 to 16% in 2007.

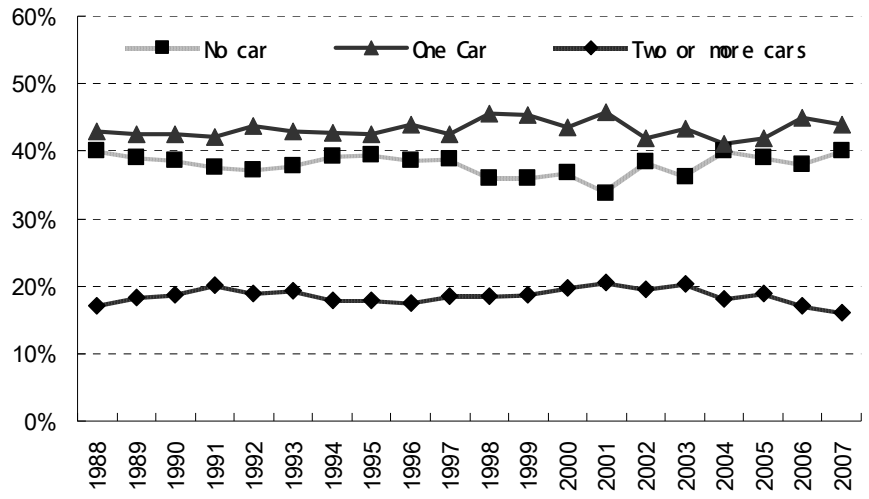


Figure 6-2 Car ownership in London (1988-2007)
Source: UK Department for Transportation, National Travel Survey, 1988-2007

6.3 Baseline MNL Models of Car Ownership

This section will first describe the data sources for the car ownership model and define the variables, and then present two MNL models: the first includes only socioeconomic variables and the second adds land use and PT access variables.

6.3.1 Data and variables

The Lifestyle and Car Dependency Survey includes a question on the number of cars owned by each household.

The dependent variable is the number of cars owned by a household, grouped into categories of “no car”, “one car”, and “two or more cars”. The “no car” option is chosen as the reference for all models. The car ownership models include the following sets of independent variables:

1) Socioeconomic and demographic: gender, age, income (in the units of GBP10,000), social grade, ethnicity, employment status, and household structure (having children or not, and number of adults);

b) Land use and public transport access: population density, land use mixture, public transportation accessibility index (PTAL), location dummy for Central, Inner or Outer London, and access to train stations.

Previous literature on car ownership models has identified other factors that have important influences on car ownership including parking availability, road congestion, cost of driving and of using PT, and accessibility to essential services etc. But they are not included in this study due to data limitations.

Models 1 and 2 are MNL models estimated in both Mplus 5.1 and Biogeme 1.8 with the identical estimation results.

6.3.2 Car Ownership Model with SES Variables

As shown in Table 6-4, household income and household size are the dominant factors affecting car ownership. As expected high income households have more cars than low income households with income being more important in determining the probability of owning 2+ cars than of owning one car. Compared to households of married couples, being single reduces the probability of owning cars and having two or more adults in the households increases the probability of owning 2+ cars. The old are more likely to own cars than other age groups. Having children increases the probability of owning cars. Being British increases the probability of owning 2+ cars.

Table 6-4 Estimation Result of Car Ownership Model 1 (Base=No Car)

Indep.Vars		2+ cars		One Car	
		Beta	t	Beta	t
SES	MALE	-0.085	-0.5	0.232	1.6
	OLD	**1.150**	**3.3**	**1.029**	**3.4**
	YOUNG	**0.574**	**2.0**	0.088	0.3
	INCX	**0.404**	**6.8**	**0.254**	**4.7**
	SGRADE	0.070	0.9	0.032	0.5
	BRITISH	**0.878**	**4.7**	0.228	1.5
	WORKING	0.449	1.5	0.254	1.0
	STUDENT	0.667	1.5	0.156	0.4
	HAVCHILD	**1.429**	**7.2**	**1.007**	**5.7**
	ADULT1	**-2.009**	**-6.2**	**-0.446**	**-2.7**
	ADULT3	**1.108**	**5.3**	-0.134	-0.7
ASC	ASC	**-3.187**	**-7.3**	**-1.057**	**-3.1**

Table 6-5 shows the goodness-of-fit for model 1. The pseudo R-square is low which is not surprising since only the SES variables are included in the model.

Table 6-5 Goodness of Fit Statistics for Model 1

# of observations	1334
Loglikelihood of the Full Model	-1229.6
# of Parameters of the Full Model	26
Loglikelihood of Null Model	-1415.6
# of Parameters of the Null Model	2
Pseudo R-square	0.131
Pseudo R-square (Adjusted)	0.114

6.3.3 Car Ownership Model with SES, Land Use and PT Access Variables

Model 2 adds the land use and PT access variables to the model. As expected, Table 6-6 shows that high population density, mixed land use and good access to train stations all reduce car ownership. Living in Outer London increases the probability of owning cars.

Table 6-6 Estimation Result of Car Ownership Model 2 (Base=No Car)

Indep. Variables		2+ Cars		One Car	
		Beta	t	Beta	t
SES	MALE	-0.179	-1.0	0.181	1.2
	OLD	**1.041**	**2.8**	**0.977**	**3.1**
	YOUNG	**0.639**	**2.1**	0.111	0.4
	INCX	**0.419**	**6.6**	**0.267**	**4.8**
	SGRADE	0.070	0.9	0.027	0.4
	BRITISH	**0.637**	**3.1**	0.058	0.4
	WORKING	**0.718**	**2.2**	0.394	1.5
	STUDENT	0.768	1.6	0.185	0.5
	HAVCHILD	**1.264**	**6.0**	**0.900**	**4.9**
	ADULT1	**-2.089**	**-6.3**	**-0.461**	**-2.7**
	ADULT3	**1.176**	**5.2**	-0.092	-0.4
Land Use & PT Access	D_POP	**-1.465**	**-4.2**	**-0.750**	**-3.0**
	ENTROP	-1.152	-0.9	**-2.916**	**-2.7**
	PTAL	-0.137	-1.2	-0.029	-0.4
	OUTERL	**1.287**	**5.2**	**0.591**	**3.2**
	ACCTRAIN	**-0.478**	**-2.6**	-0.177	-1.2
ASC	ASC	-1.850	-1.5	1.552	1.6

Table 6-7 Goodness of Fit Statistics for Model 2

# of observations	1334
Loglikelihood of the Full Model	-1149.7
# of Parameters of the Full Model	36
Loglikelihood of Null Model	-1413.1
# of Parameters of the Null Model	2
Pseudo R-square	0.186
Pseudo R-square (Adjusted)	0.162

Table 6-7 shows the goodness-of-fit for model 2. The Pseudo R-square increases to 0.162 from 0.114 in Model 1.

6.4 Incorporating Latent Factors into Car Ownership Model

Model 3 is a latent variable choice model to enhance the base model by capturing the impact on car ownership of environmental attitudes, car pride, and perception of convenience.

The latent variable choice model uses a similar methodology as in Chapter 5 but the difference is that the model also includes a feedback loop from car ownership to the latent factors.

Figures 6-3 and 6-4 illustrate the hypothesized relationships between the latent factors and car ownership:

1) The relationships among the latent factors follow a similar pattern identified in chapter 3.

2) Three latent factors *f_CarPride*, *f_Convenience* and *f_EnvTax* enter the utility function while the effect of factor *f_Env* is mediated through *f_EnvTax*.

3) Figure 6-4 includes the potential feedback loops from car ownership to the latent factors, shown by the dark arrows

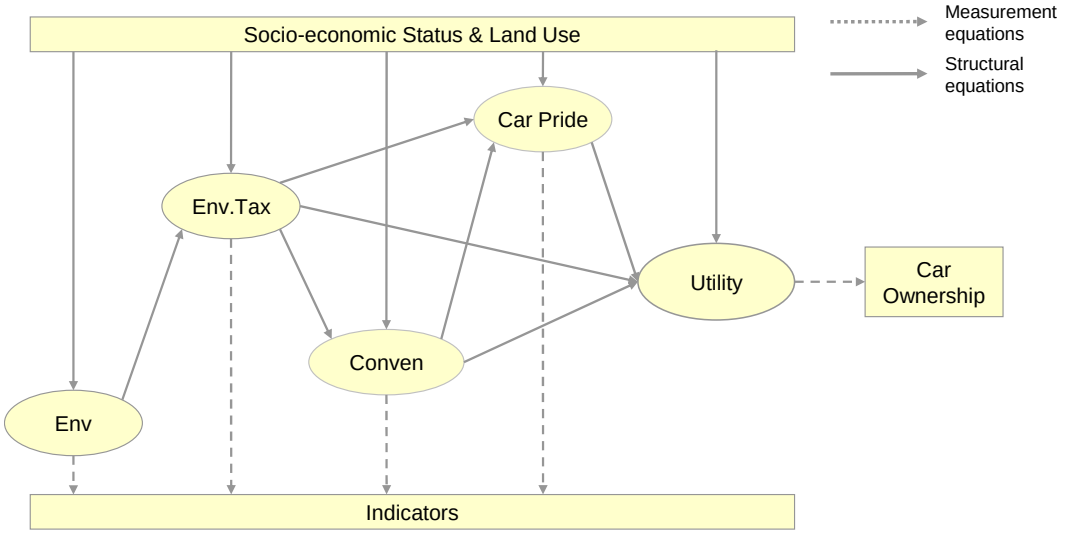


Figure 6-3 Car Ownership Model with Latent Variables without Feedback

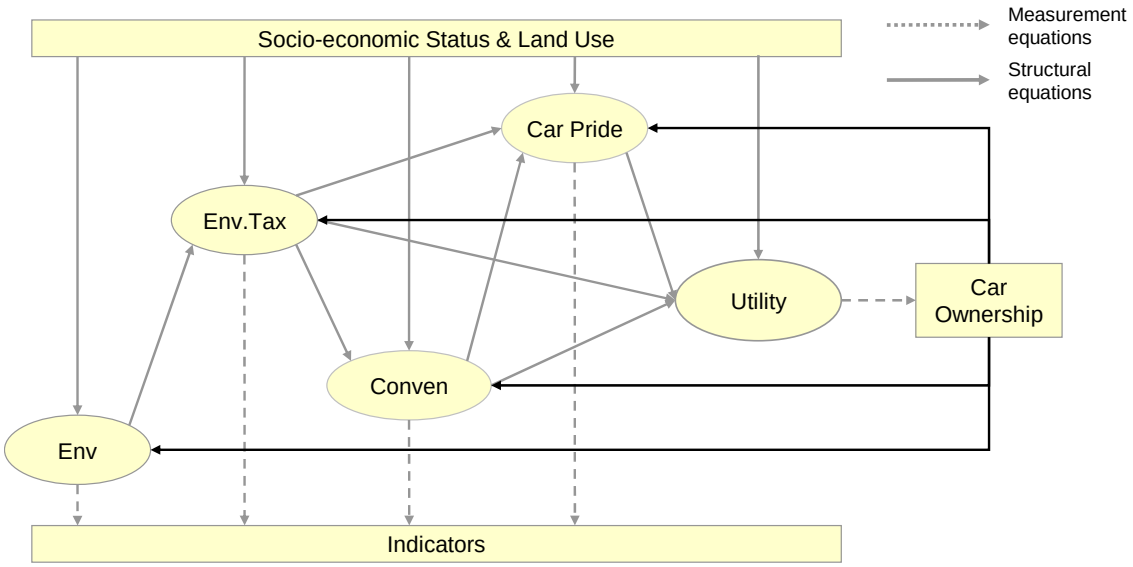


Figure 6-4 Car Ownership Model with Latent Variables with Feedback

Because the dependent variable car ownership is modeled as a nominal variable, it cannot be included directly in the structural equations for the latent factors. Instead, two dummies CarTwo (owning two or more cars) and CarOne (owning one car) are used.

Three specifications are estimated: 1) model without feedback; 2) model with feedback using CarOne as the indicator of car ownership; and 3) model with feedback using CarTwo as the indicator of car ownership. All three specifications are estimated in

Mplus. The excerpt of the Mplus code for specification 3 is included in Appendix C-2. The measurement equations for the latent factors, the interrelationships among the latent factors, the car ownership equation, and the feedback from car ownership to latent factors (if any) are all estimated at the same time. The latent factors are measured by the same sets of indicators as in Chapter 3.

Table 6-8 compares the goodness-of-fit of the three specifications. The likelihood ratio tests between specifications 1 and 2, and between specification 1 and 3 found that both models with feedback perform better than the model without feedback. The likelihood ratio test between specifications 1 and 3 is shown below:

The change in degrees of freedom is 145-141=4. The critical value of the chi-square statistics at the 1% significance level is 13.28. Twice the difference between the loglikelihood values of specifications 1 and 3 is 101.15, which is greater than the critical value.

Table 6-8 Goodness-of-fit Statistics for Three Model Specifications

Specification	1	2	3
	w/o feedback	w/ feedback by CarOne	w/feedback by CarTwo
# of observations	1334.0	1334.0	1334.0
Loglikelihood of the Full Model	-30687.4	-30673.2	-30636.8
# of Parameters of the Full Model	141	145	145
Loglikelihood of Null Model	-31047.541	-31038.786	-31017.237
# of Parameters of the Null Model	107	111	111
Loglikelihood of the Base Model	-1413.062	-1413.062	-1413.062
Pseudo R-square	0.255	0.259	0.269
Pseudo R-square (Adjusted)	0.231	0.235	0.245

Specification 3 is obviously better than specification 2 because with the same number of parameters, the loglikelihood in specification 3 is (-30636.8)-(-30673.2) =36.4 higher than in specification 2. This is also evidenced by the increase of the adjusted pseudo R-square from 0.235 to 0.245. The dummy CarTwo is more useful in representing the feedback from car ownership to the latent factors than the dummy CarOne.

Therefore specification 3 is chosen as the preferred model. The estimation results based on specification 3 are reported in Tables 6-9 through 6-11. Table 6-9 reports the impact of the latent factors on car ownership and Table 6-10 reports the impact of car

ownership on the latent factors. Causalities in both directions are confirmed by the significant coefficients of the causal links in these tables:

All three latent factors are significant in determining car ownership with the expected signs: car pride and perception of convenience significantly increase the probability of owning cars. Positive environmental attitudes reduce the tendency to own cars.

Car ownership is significant or marginally significant in determining two of the four latent factors: high car ownership decreases people's willingness to pay tax in order to protect the environment (*f_EnvTax*) and increases the perception of car being more convenient than public transportation.

Table 6-9 the Impacts of Latent Variables on Car Ownership

Indep.Vars		2+ Cars		One Car	
		Beta	t	Beta	t
Latent Factors	F_ENVTAX	-0.860	-1.6	-0.733	-3.6
	F_CONVEN	2.966	4.2	1.755	5.5
	F_CARPRIDE	0.862	1.9	0.427	2.5
SES	MALE	-0.107	-0.4	0.272	1.5
	ELDER	1.554	3.4	1.419	3.6
	INCX	0.413	5.3	0.254	4.0
	SGRADE	0.177	1.6	0.117	1.4
	BRITISH	0.855	3.4	0.237	1.3
	WORKING	0.963	2.3	0.506	1.5
	STUDENT	1.425	2.5	0.377	0.8
	HAVCHILD	1.188	4.3	0.835	3.8
	ADULT1	-2.513	-6.1	-0.701	-3.2
	ADULT3	1.595	5.8	0.053	0.2
Land Use & PT Access	D_POP	-1.633	-4.0	-0.871	-2.9
	ENTROP	-1.890	-1.1	-3.281	-2.6
	OUTERL	0.882	2.8	0.349	1.6
	ACCTRAIN	-0.234	-1.0	-0.061	-0.3
ASC	ASC	-2.176	-1.4	1.763	1.5

Table 6-10 the Impact of Car Ownership on Latent Factors

Indep. Variables	F_ENV		F_ENVTAX		F_CONVEN		F_CARPRIDE	
	Beta	t	Beta	t	Beta	t	Beta	t
CARTWO	-0.122	-1.4	-0.183	-1.9	0.268	2.6	0.131	0.9

Table 6-11 describes the relationships between latent factors. *F_Env* positively influences *f_EnvTax* while *f_EnvTax* negatively influences car pride and perception of convenience. Perception of car convenience increases car pride.

Table 6-11 Standardized Coefficients for the Connections between Latent Factors

Dep. Vars	Indep Vars	Beta	t
F_CARPRIDE	F_CONVEN	0.213	3.1
F_CARPRIDE	F_EnvTax	-0.366	-6.5
F_CONVEN	F_EnvTax	-0.267	-6.1
F_EnvTax	F_ENV	0.473	8.1

Table 6-12 summarizes the model fits for Models 1, 2 and 3. Adding land use and PT access variables increase the adjusted R-square by 42% from 0.114 to 0.162 and adding latent variables increase the adjusted R-square by further 42% to 0.231. Finally introducing feedback increases the adjusted R-square by further 6%.

Table 6-12 Goodness-of-Fit Comparison between Models 1, 2 and 3

Model ID	Descriptions	Adjusted R^2
Model 1	MNL Model with SES Variables	0.114
Model 2	MNL Model with SES, Land Use and PT Access	0.162
Model 3 Spec.1	Choice Model with Latent Variables but no Feedback	0.231
Model 3 Spec.3	Choice Model with Latent Variables and Feedback	0.245
% increase from Model 2 to Model 1		42%
% increase from Model 3 (specification 1) to Model 2		42%
% increase from Model 3 (specification 3) to Model 3 (specification 1)		6%

6.5 Latent Class Models to Test Heterogeneity in Traveler Preferences

Two latent class models are estimated to test heterogeneities in the sensitivity to two latent factors influencing car ownership: car pride and perception of convenience.

6.5.1 Heterogeneity in the Sensitivity to Car Pride

Model 4 examines whether the impacts of car pride on car ownership differ across the population. The results are summarized in Tables 6-13 through 6-15. The excerpt of the Mplus code for Model 4 is included in Appendix C-3. The estimation procedure is the

same as the latent class models in Chapter 5. Two latent classes are identified in Model 4. Car pride is important for both classes but about 10% of households value car pride much more than the remaining 90% (the coefficients are three to four times larger). In effect, for those 10% of all households, car pride is one of the most important reasons to buy a car, particularly a second car.

Table 6-13 Coefficients that are the same across classes

Indep. Variable		2+ Cars		One Car	
		Beta	t	Beta	t
SES	MALE	-0.100	-0.5	0.253	1.5
	ELDER	**1.210**	**2.9**	**1.093**	**3.0**
	YOUNG	0.564	1.7	0.093	0.3
	INCX	**0.422**	**6.0**	**0.262**	**4.4**
	SGRADE	0.076	0.9	0.036	0.5
	BRITISH	**0.728**	**3.4**	0.128	0.8
	WORKING	**0.775**	**2.2**	0.410	1.4
	STUDENT	0.776	1.5	0.129	0.3
	HAVCHILD	**1.400**	**6.0**	**0.957**	**4.8**
	ADULT1	**-2.222**	**-6.1**	**-0.534**	**-2.8**
	ADULT3	**1.276**	**5.1**	-0.046	-0.2
Land Use & PT Access	D_POP	**-1.525**	**-4.3**	**-0.833**	**-3.1**
	ENTROP	-1.983	-1.3	**-3.590**	**-3.0**
	PTAL	-0.071	-0.5	0.036	0.4
	OUTERL	**1.314**	**4.8**	**0.570**	**2.9**
	ACCTRAIN	**-0.437**	**-2.2**	-0.136	-0.8
ASC	ASC	**-3.638**	**-2.6**	0.882	0.8

Table 6-14 Coefficients that differ across classes

Latent Classes	Indep. Variable	2+ Cars		One Car	
		Beta	t	Beta	t
Class 1	F_CARPRIDE	**1.311**	**5.8**	**0.716**	**4.7**
Class 2	F_CARPRIDE	**5.189**	**2.9**	**2.219**	**2.1**

Table 6-15 Class Counts

Classes	Counts	%
1	1203	90%
2	129	10%
Total	1332	100%

6.5.2 Heterogeneity in the Sensitivity to Convenience

Model 5 examines heterogeneity in the influence of convenience on car ownership. Two classes of people are distinguished. Table 6-16 shows that for both classes, the perception of car convenience increases the probability of owning cars, and for people in class 2 (40% of the population), the perception of convenience is twice as important in determining car ownership as for those in class 1 (60% of the population). Tables 6-17 and 6-18 show the results of the class membership model which indicates that people with high income, having children, or living in Outer London are more likely to belong to class 2 and people who have good access to train services are more likely to belong to class 1. The factor *f_InCtrl* in the class membership model is not significant, which shows that the personality of "being in control" does not influence the sensitivity to perception of convenience.

Table 6-16 Coefficients that differ across classes

Latent Classes	Indep. Variable	Two Cars or More		One Car	
		Beta	t	Beta	t
LC1	F_CONVEN	3.151	7.3	2.310	6.2
LC2	F_CONVEN	6.446	2.8	5.863	2.6

Table 6-17 Class Membership Model

Indep. Variable		Class #1	
		Beta	t
SES	YOUNG	-0.249	-1.1
	INCX	-0.099	-2.4
	HAVCHILD	-0.686	-4.5
	OUTERL	-0.922	-5.5
	ACCTRAIN	0.568	3.9
Latent Variable	F_INCTRL	0.300	0.9
ASC	ASC	1.373	5.8

Table 6-18 Class Counts

Classes	Counts	%
1	799	60%
2	533	40%
Total	0	0%

6.6 Conclusion

The chapter incorporated into the car ownership model latent factors including environmental attitudes, car pride and perception of car convenience. These latent factors significantly increase the explanatory power of the car ownership models and mutual dependencies are identified between car ownership and traveler preferences. This chapter also tested the heterogeneity in people's response to these latent factors using latent class models and found that people's responses to car pride and perception of convenience do indeed vary across the population.

Chapter 7. Summary and Conclusions

The final chapter is organized as follows. Section 7.1 summarizes the behavioral findings from the models in Chapters 3 through 6. Section 7.2 presents a few hypothetical scenarios of preference changes and illustrates the magnitude of their impacts on travel behavior. Section 7.3 discusses the overall policy implications and sections 7.4 and 7.5 discuss how to embed traveler preferences in transportation planning from the perspectives of preference accommodating and preference shaping. Sections 7.6 and 7.7 describe the limitation of the current research and the future research directions. Section 7.8 concludes with the discussion on planners' role and the application of this research in fast urbanizing countries such as China.

7.1 Summary of Behavioral findings

This dissertation proposes a structure for analyzing traveler preferences that includes people's socioeconomic and demographic characteristics, personality and attitudes, and perceptions. This structure is used to organize the plethora of factors that influence travel behavior and to distinguish the factors that are internal to the decision makers from those that are external.

A set of eight factors are presented as the latent elements of travel preferences to illustrate the structure, including two personality traits; three environmental attitude factors and car pride; and two perceptual factors of convenience and comfort.

A MIMIC model quantifies the eight latent factors based on psychometric indicators, and examines the interrelationship among the eight factors as well as between them and the socioeconomic and demographic variables. It is found that

(A) There are significant correlations between socioeconomic and demographic variables and latent factors

(B) Despite these correlations, the socioeconomic and demographic variables do not explain much of the variation in the latent factors. Personality, attitudes and perceptions are characteristics of individuals that are distinct from the socioeconomic and demographic variables and which need separate measures.

The dissertation then presents three applications that incorporate eight latent factors into travel demand analysis of three critical aspects of travel behavior: aggregate car mode share and trip frequency, disaggregate mode choice and car ownership.

Findings based on the three applications include:

(C) Incorporating the latent variables significantly improves the overall exploratory power of the transportation models and different latent factors play different roles depending on the aspect of travel behavior

(D) The effect of certain SES variables on travel behavior may change significantly after latent variables are introduced into the model in which both their direct effect and indirect effects via latent variables are explicitly examined

(E) Unobserved heterogeneities exist not only for preferences with respect to the observed variables such as travel time, but also for the latent factors such as car pride and perception of convenience

(F) In many cases, the models considering the feedback from behavior to preferences are superior to the models assuming only one way causality. Mutual dependencies between travel preferences and behavior are identified and the direction and strength of the causal connections are modeled explicitly. Depending on the specific latent factors and aspect of travel behavior, the

causal relationships could be from preferences to behavior, from behavior to preferences, or be significant in both directions concurrently

These three applications also demonstrate in terms of methodology that

(G) A hierarchical relationship among latent factors can be simultaneously estimated with the discrete choice model in the Generalized RUM framework (Walker and Ben-Akiva 2002)

(H) Latent variable and latent class modeling techniques can be combined to test the unobserved heterogeneities in travelers' sensitivity to latent variables and define latent class membership with latent variables

(I) Causal relationships between behavior and preferences can be specified in the SEM for continuous dependent variables (such as car mode share and car trip frequency) and in the hybrid SEM and discrete choice model for categorical variables (such as car ownership)

7.2 Hypothetical Scenarios of Preference Change

To provide a concrete sense of how much preference changes may matter to travel behavior, this dissertation presents a few hypothetical scenarios of preference change and examines their impacts on car ownership.

Three scenarios of preference change are developed including:

1) People's general environmental attitudes and support for government's actions and taxations to protect the environment continue to improve. Specifically it is assumed that the factor score of *f_EnvTax* increases uniformly for everyone by one standard deviation, which is 0.55. Note that the latent factors have the same scale as their indicators. Each indicator has five levels: strongly agree, slightly agree, neither agree or disagree, slightly disagree and strongly disagree which are coded as 2, 1, 0, -1 and -2, respectively. So a stand deviation (0.55) is about half a level.

2) People's sense of car pride continues to decrease. Specifically the factor score of *f_CarPride* decreases uniformly for everyone by one standard deviation, which is 0.60.

3) Mix of scenarios 1 and 2 but both *f_EnvTax* and *f_CarPride* change only by half standard deviation

Two more scenarios are developed as base cases for comparison

4) Population density increases by one standard deviation

5) Household income increases by one standard deviation

The impact of preference changes on car ownership is assessed using the car ownership Model 4 developed in Chapter 6. The utility functions in Table 6-9 are applied to calculate the probability of owning 0, 1, and 2+ cars in each scenario.

The scenario tests do not discuss how and why these preference changes happen and only examine their impacts on travel behavior if they were to happen. The scenario tests do not consider feedback from behavior to preferences and assume one-way causality from preferences to behavior.

7.2.1 What if environmental attitudes continue to improve?

Table 7-1 shows the current distribution of the factor *f_EnvTax* and its distribution in Scenario 1. Table 7-2 shows the change of the proportions of population who own 0, 1, 2+ cars for the whole London and by Inner and Outer London.

First the aggregate car ownership reduces substantially: the proportion of the population who does not have a car increases by 5.1 percentage points. The proportion who own one car decreases by 3.4 percentage points and the proportion who own 2+ cars decreases by 1.8 percentage points.

Second, the impact on Inner London is greater than Outer London.

Third, while in Inner London the reduction is more from one car owners than 2+ car owners, in Outer London the reduction is roughly balanced between one car owners and 2+ car owners.

Table 7-1 Distributions of *f_EnvTax* in Scenario 1

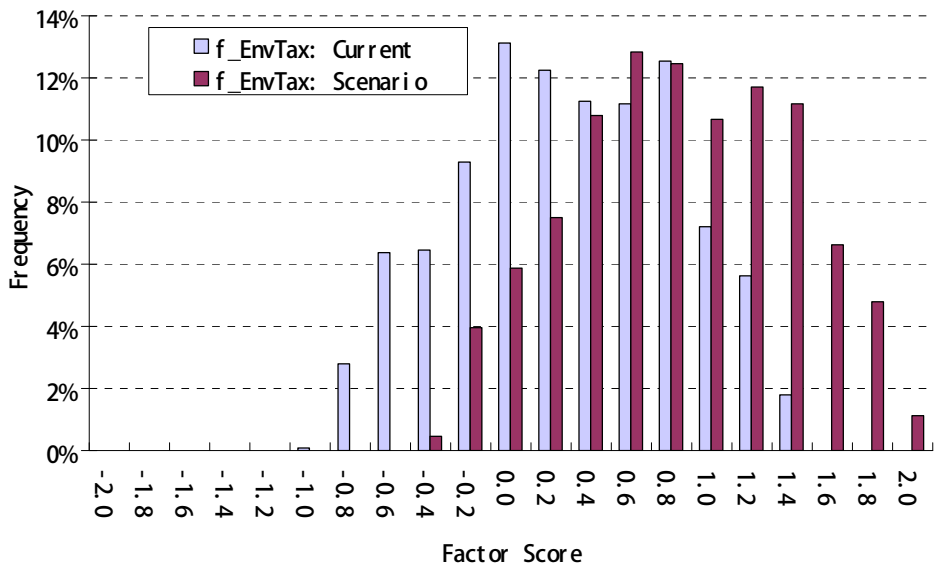


Table 7-2 Change of Car Ownership Probability in Scenario 1 by Region

Region	Cars owned	% of Population		
		Current	Scenario	Change
Whole London	0	25.3%	30.4%	5.1%
	1	47.1%	43.7%	-3.4%
	2+	27.6%	25.8%	-1.8%
Inner London	0	42.7%	49.5%	6.8%
	1	45.6%	40.2%	-5.4%
	2+	11.7%	10.3%	-1.4%
Outer London	0	16.5%	20.8%	4.3%
	1	47.8%	45.5%	-2.3%
	2+	35.7%	33.7%	-2.0%

Figure 7-1 plots the distribution of the probabilities of owning 1 car within the population before and after the *f_EnvTax* change. Those who have a lower probability of owning one car increase and those who have higher probability of owning one car decrease.

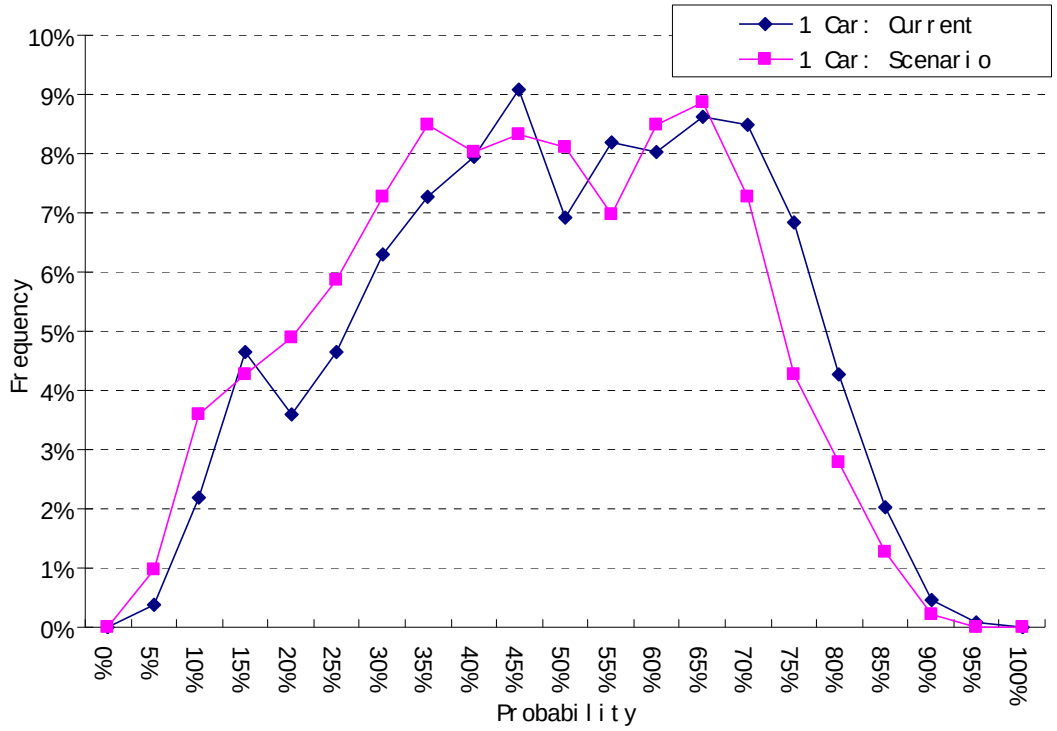


Figure 7-1 Distribution of the Probabilities of Owning 1 Car

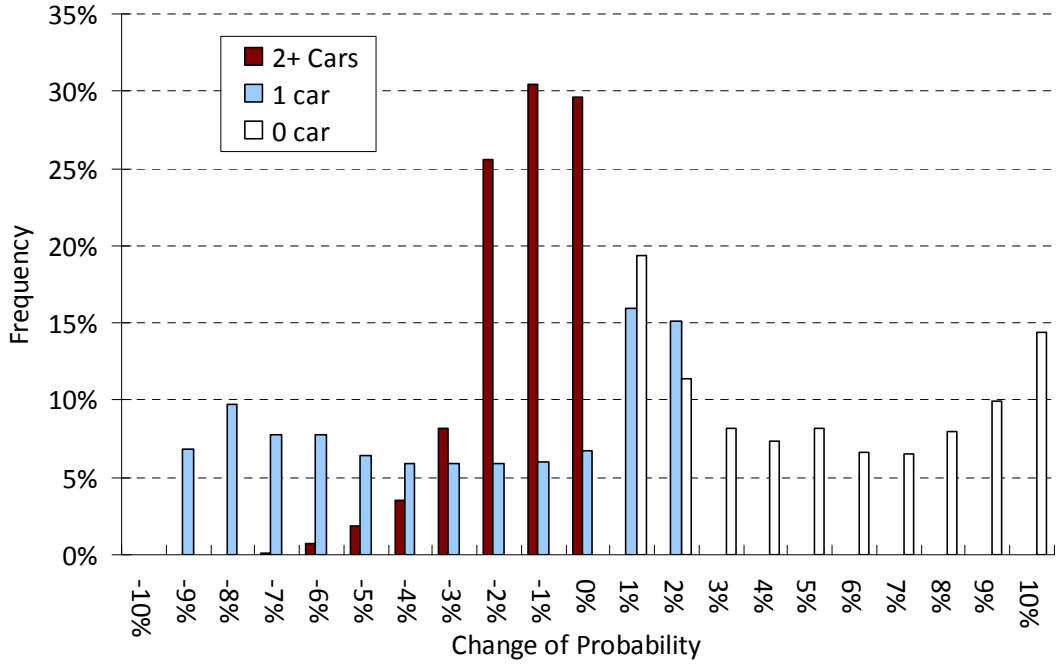


Figure 7-2 Distribution of the change of probabilities in Scenario 1

Figure 7-2 plots the distribution of the change of probabilities before and after *f_EnvTax* changes. For probabilities of not owning a car, the changes are all positive; for probabilities of owning one car, most of the changes are negative and have a wide range but some are positive, which refer to those who change from owning 2+ cars to owning 1 car; for probabilities of owning 2+ cars, the changes are negative and most of them concentrate in a tighter range of -3%~0%.

7.2.2 What if car pride becomes less important?

Figure 7-3 plots the current distribution of *f_CarPride* and its distribution in scenario 2, which assumes the decrease of car pride uniformly across the population by one standard deviation. Table 7-3 shows the change of proportions of population who own 0, 1, 2+ cars for the whole London and by Inner and Outer London.

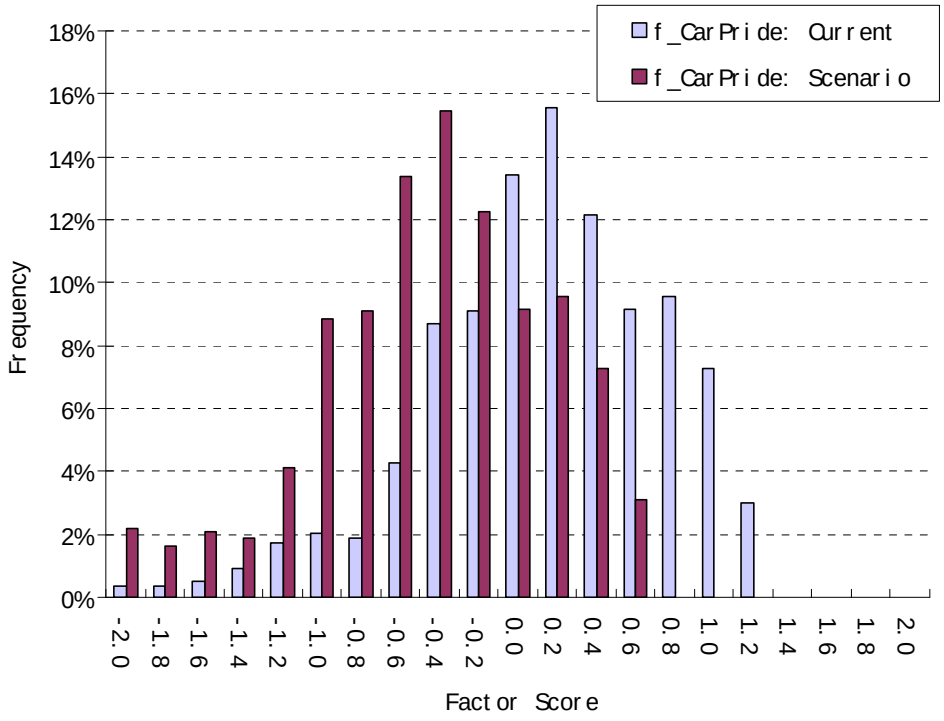


Figure 7-3 Distribution of *f_CarPride* in scenario 2

Table 7-3 Change of Car Ownership Probability in Scenario 2 by Region

Region	Cars owned	% of Population		
		Current	Scenario	Change
Whole London	0	25.3%	29.0%	3.7%
	1	47.1%	47.2%	0.1%
	2+	27.6%	23.8%	-3.9%
Inner London	0	42.7%	47.5%	4.8%
	1	45.6%	43.3%	-2.3%
	2+	11.7%	9.3%	-2.4%
Outer London	0	16.5%	19.6%	3.2%
	1	47.8%	49.2%	1.4%
	2+	35.7%	31.2%	-4.6%

The aggregate car ownership reduces substantially, particularly the 2+ car owners. This is different from the result in scenario 1, where the reduction is more from the 1 car owners. The impacts vary significantly across region: while in Inner London the reduction is balanced between one car owners and 2+ car owners, in Outer London the change is from owning 2+ cars to owning 1 car or no car.

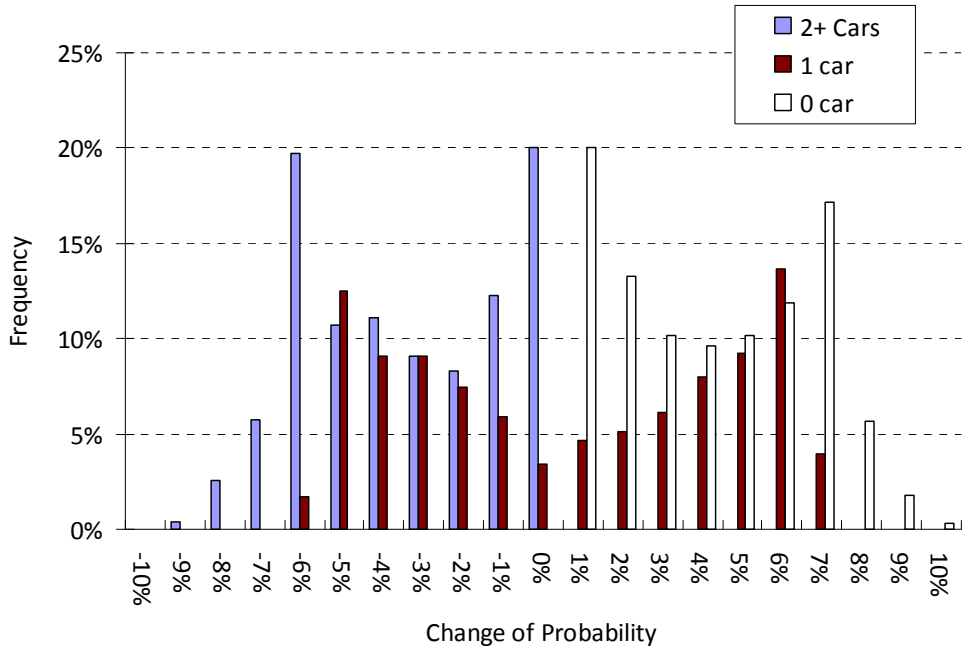


Figure 7-4 Distribution of the change of probabilities in Scenario 2

Figure 7-4 offers more details of the changes of probabilities. The changes of the probabilities of not having a car are all positive. The changes of the probabilities of owning two cars are all negative. The changes of the probabilities of owning one car have both positive and negative cases. This reflects that some 2+ cars owners become one car owner and some one car owners become not having a car.

7.2.3 Summary of all scenarios

Changes in environmental attitudes and car pride both have significant impacts on car ownership. But their impacts are different both in terms of location and in terms of targeting one car owners or 2+ cars owners. Table 7-4 summarizes the impacts on car ownership in the five scenarios. The key finding is the impacts of the environmental attitudes or car pride changes are on a par with those of the changes in population density and household income. For example, one standard deviation increase of *f_EnvTax* almost offsets the impact of one standard deviation of the household income increase.

Table 7-4 Summary of Scenarios

Region	Cars owned	Current proportion	Changes in scenario				
			1	2	3	4	5
			f_EnvTax	f_CarPride	1+2 mix	D_POP	INCOME
Whole London	0	25.3%	5.1%	3.7%	4.4%	4.5%	-5.7%
	1	47.1%	-3.4%	0.1%	-1.6%	-0.4%	0.8%
	2+	27.6%	-1.8%	-3.9%	-2.8%	-4.2%	4.9%
Inner London	0	42.7%	6.8%	4.8%	5.8%	5.8%	-8.0%
	1	45.6%	-5.4%	-2.3%	-3.9%	-3.2%	4.4%
	2+	11.7%	-1.4%	-2.4%	-1.9%	-2.6%	3.6%
Outer London	0	16.5%	4.3%	3.2%	3.7%	3.9%	-4.5%
	1	47.8%	-2.3%	1.4%	-0.5%	1.1%	-1.0%
	2+	35.7%	-2.0%	-4.6%	-3.3%	-5.0%	5.6%

7.3 Policy Implications

The direct policy and planning implications of the behavioral findings and the modeling techniques include:

(A) Many latent factors can be as important as the observed variables such as SES and land use in explaining travel behavior. Ignoring them in the planning process could result in serious errors in model estimation and application. A systematic effort is needed in transportation planning to monitor traveler preferences in customer research, assess the impacts of traveler preferences in project evaluation, understand their changes due to societal trends or policy intervention, and forecast their evolution in future planning.

(B) Incorporating these latent factors not only improves the explanatory power of the transportation models, but also provides more realistic descriptions of travelers' decision making. These behavioral findings enrich our understanding of traveler preferences, expanding it from the economic and demographic domains to the cultural and psychological domains including environmental attitudes, personality traits and car pride.

(C) Correspondingly these enhancements to the models expand the range over which transportation models can be used to inform policy debate and planning decisions, and connect transportation planning more closely to the latest social and cultural agenda such as global warming.

The following will discuss the extended implications that are inspired and suggested while not necessarily directly evidenced by the findings in the dissertation. These extended implications will be discussed from two complementary perspectives: planning as preference accommodating and planning as preference shaping.

A passive view regards transportation planning as preference accommodating: to respect people's preferences by aligning what we assume about how people behave with how they actually behave. A richer set of factors in people's preferences requires corresponding expansion in our planning activities to account for them.

An active view regards transportation planning as including preference shaping. Transportation agencies often focus on influencing behavior by changing transportation

systems, e.g., expanding the network by building Cross-Rail in London or altering the price structure by imposing Congestion Charging. Behavior might also be changed by promoting desirable features of the existing transportation system, informing people of the consequences of certain travel behavior, and awakening people's environmental conscience. The possibility of actively influencing traveler preferences opens a whole new set of options that have been largely overlooked in the past, as well as a new set of ethics and "big government" concerns.

Combining both perspectives, this chapter argues that by ignoring the importance of traveler preferences, not only may we make serious mistakes in the planning, modeling and appraisal processes, but we may also fail to recognize significant opportunities to mitigate or solve transportation problems by influencing and exploiting changes in people's preferences.

7.4 Preference accommodating

7.4.1 Reflection on the four barriers

Our discussion started with the gap between the rich set of factors that enter into travelers' decision making and those that transportation planners actually include in their models. The gap often points to the latent factors of the traveler preferences such as attitudes, personality and perceptions. Chapter 2 identifies four main barriers that have prevented these latent factors from being considered in transportation planning. These barriers in practice are reflections of the similar gap in research which, until recently, has treated travel preferences as a black box and focused on the mapping between transportation system attributes and travel behavior without too much attention to the internal working of traveler preferences.

But in addition to these technical barriers, there are also important attitudinal barriers within the transportation agencies. The mentality of transportation planners that regards these factors as "too soft" does not help close this gap. Consistent with the imbalance between research focused on transportation systems and that focused on

traveler preferences, there exists more disparity in the transportation planning and policy practice: most agencies monitor their transportation systems and plan their future changes reasonably well, but few concern themselves with understanding traveler preferences beyond their economic and demographic characteristics, or the possible changes of traveler preferences over time.

The literature review in Chapter 2 has shown that recent theoretical and statistical innovations have reduced these technical barriers and provided a methodological foundation for transportation planners to incorporate these latent factors into transportation planning. This dissertation has also demonstrated this possibility with eight latent factors of traveler preferences and their applications in three critical aspects of travel behavior.

To incorporate traveler preferences into transportation planning to a greater extent requires a systematic effort throughout the functional departments of transportation agencies such as the customer research team, the project evaluation team, the policy development team, and the modeling and forecasting team.

7.4.2 Implications for customer research

Customer research teams in many transportation agencies have been paying attention to traveler preferences in both their socioeconomic elements and their psychological elements for some time. However there are three problems in most customer research practice which still need to be addressed:

1) The methods to design surveys and measure latent factors of travel preference are ad hoc and inconsistent. Unlike the socioeconomic variables or travel diaries, for which reasonably stable variable definitions and survey designs exist, the questionnaires about psychological factors do not have standards. Different latent constructs are included in different years and by different agencies. Different indicators are used to measure the same latent constructs. Specific wording of the indicators may vary greatly across surveys. Much of this diversity is for legitimate reasons: different latent psychological

factors get emphasized in different times and different cities; appropriate indicators for the same latent construct may differ according to local context, etc. But these inconsistencies may have significant influence on the accuracy and stability of the measurement of the latent factors.

This is one of the most important reasons that psychological factors also tend to be discredited by transportation decision makers. The set of chosen factors looks random; the definition of the factors looks random; the years in which the factors are surveyed look random; the results are often contradictory with those from other researchers. Therefore even though many psychological factors are recognized as important and quoted in qualitative debates, they never enter the quantitative analysis and effectively influence decision making.

This ad hoc and inconsistent nature also has severe consequences on research. The impossibility of firmly measuring the latent factors and comparing them over time or across agencies heavily limits the range and depth of research which can be readily conducted.

2) The statistical capacity to analyze the survey results is limited. After the customer surveys are conducted and results collected, the analysis of the results is often only at a superficial level with either univariate histograms or cross-tabulations being employed. These types of analyses are important to provide a starting point for the understanding of the latent factors but will not help uncover the underlying mechanism through which these factors operate, interact and influence travel behavior. More advanced techniques are needed to fully exploit the meanings of the survey results.

3) Gap between the outputs of the Customer Research team and the inputs for the Demand Modeling team

Customer Research teams often carry out a large number of surveys and studies which cover a wide range of topics. For example TfL carries out over 100 surveys or research projects each year. The demand modeling teams often need only a handful of

parameters to be included in their analytic models. But the outputs from the Customer Research are rarely digested into parameters that can be taken as input by the demand modeling teams. This could be due to the customer research team not analyzing the results deeply enough, the limited scope of the demand models to consider the findings from customer research, or lack of collaboration between the two teams.

7.4.3 Implications for demand modeling

Travel demand models in most transportation agencies consider only SES variables and travel time and travel cost. The parameters that represent people's sensitivities to these variables are often assumed as fixed and are rarely updated.

To incorporate the latent factors into the transportation models may prove a difficult task in the near future. Nevertheless, suggested below are a few steps that are required.

1) Update the model structure to include the capacity to handle latent factors. While the methodology exists, there is no implementation of models with latent factors in transportation agencies.

2) Update the model structure to account for heterogeneity within the population, both the observed heterogeneity, which many agencies have partially accounted for with population segmentations, and unobserved heterogeneity.

3) Update model parameters regularly to reflect changes in traveler preferences.

4) Prepare the data infrastructure. The data on latent factors need to be either collected by the customer research team, or obtained from private firms or government departments outside the transportation agencies. The data on latent factors also need to be accompanied by fine-grained geographic information and associated land use data so that they can be connected to time and location at the level of detail that matters to individuals.

7.4.4 Implications on project appraisal

The implications of the latent factors on project appraisal are bi-directional.

On one hand, the key output variable in transportation project appraisal is the travel time saving and its monetary value. Latent factors influence travel behavior and consequently incorporating latent factors in project appraisal may alter the appraisal results.

On the other hand, transportation projects, be they new infrastructure and services or improvements to existing ones, may affect people's perceptions of and attitudes towards transportation modes and their usage. For example, Congestion Charging not only explicitly increases the cost of car use into Central London, but also sends a message to Londoners that driving imposes negative externalities on the city and is discouraged by society. The latter effect may produce social pressure that deters car use in a distinct way from the direct monetary effect.

Project appraisers often encounter difficulty in assessing those projects that do not directly influence travel behavior through changes in travel time or travel cost. For example, the Smart Travel Demand Management (STDM) Program aims to promote more sustainable travel behavior without financial incentives or infrastructure or service changes. The tools STDM employs are persuasion, demonstration, education, information, peer pressure, competition, goal setting, commitment, exemplar behavior, etc, which aim to change behavior by changing attitudes such as exploiting people's environmental consciousness. Project appraisers use standardized transportation demand models to calculate benefit and cost of a project. But none of the STDM's tools can be effectively quantified in the traditional transportation models except through the rather arbitrary adjustment to the model inputs and parameters such as the trip generation rates or modal constants (Transport for London 2006, Reflecting Soft TDM Impact in LTS). Incorporating some latent factors into transportation models is a first step toward the effective appraisal of such projects.

7.5 Preference shaping

This section will discuss the advantages of shaping traveler preferences over changing transportation system, the concerns over preference shaping, the reality of preference shaping, the justification of democratic preference shaping, and the practicality of preference shaping in the planning processes.

7.5.1 Advantages of preference shaping

One central debate on the urban transportation problem and its wider environmental implication is the conflict between the individual and short-term interest and the collective and long-term interest. Facing this conflict, a commonly employed policy intervention is to charge the full cost of the individual action, such as congestion charging or pollution fee.

These types of interventions often encounter serious resistance from the public and rarely survive the political process. Those who are charged fees to compensate the negative externality feel their welfare is reduced and they are victims of the policy intervention. In their mental accounting, the long term benefit to society at large can hardly offset the immediate loss to the individuals themselves.

But once the possibility of encouraging more appropriate preferences is introduced, travelers need not feel sacrificed to achieve the social good. The difference between charging full costs and changing preferences is that in the former case, travelers end up feeling deprived and unhappy, whereas they may feel enlightened and happy after being educated into the joy of environment-friendly travel behavior such as walking and cycling.

Compared to infrastructure investment or service improvement, preference changes may bring potential efficiency gains. It may be possible to make small social investments that will affect which types of behavior bring enjoyment to travelers, reducing the scale of the environmental impacts without decreasing, perhaps even increasing, levels of traveler welfare.

This research suggests a need to rethink the balance between our efforts and investments targeted at improving the physical transportation system and those targeted at accommodating and/or influencing people's preferences.

Preference change can be thought of as an alternative to relying solely on price to influence behavior. Both influence behavior, and both are subject to imperfections. We may wish to influence both prices and preferences in order to achieve our long-term social goals.

Value of preference shaping goes beyond just changing behavior. It may increase happiness without changing behavior or increases policy acceptance without changing policy contents.

7.5.2 Concerns over preference shaping

Given the above advantages of preference shaping, why is it rarely discussed in economics and public policy?

The possibility of travel preference change and the attempt to influence travel preference through transportation policy impose two challenges: one is methodological, which undermines the fixed-preference assumption in classical travel behavior models; the other is ethical, which raises legitimate concerns regarding the possible manipulation of preferences in service of narrower-than-public interests. (Norton et al 1998). Both challenges give rise to the fact that preference change and preference shaping are rarely discussed in transportation policies.

(A) Methodological convenience

The conventional economic paradigm assumes that preferences are exogenous to the economic system, and that the economic problem consists of optimally satisfying these preferences. The preference change is troublesome for classical economic analysis because the optimality criteria have to be redefined if preferences are expected to change.

Tastes and preferences usually do not change rapidly and in the short term this assumption makes sense. However, transportation planning is an inherently long term problem (20~30 year horizon common in transportation plans) and in the long term, travel preferences are subject to the influence of education, advertising, and changing cultural norms, so it no longer make sense to assume preferences are fixed.

Enough empirical evidence from psychology exists to demonstrate that the fixed preference assumption is not a correct empirical generalization about human preferences and it does not reflect the nature of preference as a psychological state (Tversky et al 1990, Tversky and Kahneman 1981, Kahneman and Snell 1992, Kahneman 2003). Therefore fixed preferences can be regarded primarily as a methodological assumption to retain mathematical simplicity and expand the explanatory scope of economic theory.

The usefulness of this assumption decreases when we discuss long term transportation planning and travel preference itself becomes the object of the discussion, particularly when the fixed-preference assumption limits the range of “available” and “acceptable” policy options, while the possibility of preference change may offer many more potential policy options to address urban transportation problems.

Rational analysis of preferences is viewed as exogenous in economics but is endogenous to social sciences in general. Travel behavior models, which drive most transportation agencies’ planning practice, exclude the analysis of preference change because the models are by and large economic models. This signifies the need to expand the scope of disciplines from which transportation policy and planning draw insights to include psychology, sociology and broader social science. When the existing method does not work, we need to upgrade the method, rather than limit the problem to be examined. Preference change causes methodological inconvenience in travel behavior modeling but this should not be a reason to preclude preference change from being discussed in transportation policy and planning.

(B) Consumer sovereignty as commitment to democracy

Even after we relax the fixed preference assumption and respect the fact that travel preferences do change, we will encounter the more difficult ethical challenge: changes in preferences are directed by individuals, not by an outside agent. Nobody, not philosophers, not social scientists, not politicians, and certainly not transportation planners, are justified in telling individuals what their preferences should be. This notion of consumer sovereignty requires that we give people what they want and that there is no need to understand why people want why they want. The question is only how to satisfy their desires as efficiently as possible (Norton et al 1998).

A commitment to democracy demands that we respect each individual's right to their own beliefs as an element of their right to freedom of belief and of speech. Free preference formation is seen as an important element of democracy.

The discussion of preference shaping therefore invites skepticism regarding the evaluation and criticism of individual preferences, and raises legitimate ethical concerns regarding the possible manipulation of preferences in service of narrow special interests. Randall (1988) claims if we set out to evaluate preferences, we have taken a giant step down the road toward paternalism, expertism, and perhaps even totalitarianism. To influence preferences of individuals therefore becomes a taboo in public policy discussion.

7.5.3 Justification of democratic preference shaping

First, what is the reality in terms of preference shaping? The fact is that travel preferences are under multiple continuous influences: business advertisements, political propaganda, peer pressure, education and cultural trends. For example, the automobile industry spends hundreds of millions of dollars on advertisement to influence traveler preferences. These efforts may produce undesirable effects. In Noam Chomsky's words (2008),

The point of the advertising is to delude people with the imagery and, you know, tales of a football player, sexy actress, who you know, drives to the moon in a car or something like that. But, that's certainly not to inform people. In fact, it's to keep people uninformed. The goal of advertising is to create uninformed consumers who will make irrational choices.

When traveler preferences are being shaped by these various forces for various purposes, should transportation planners take part and engage the public in an open dialogue to discuss and evaluate these influences with a broader social interest in mind?

Second, as Thaler and Sunstein (2003) argue, some level of paternalism is inevitable. In many situations, some organizations, either public or private, must make choices that will affect the choices of some other people. When paternalism seems absent, it is usually because the starting point appears so natural and obvious that its preference-shaping effects are invisible to most observers. But those effects are nonetheless there.

In fact, transportation planners have been "shaping preferences" by one means or another for many years without calling it that. There are grounds for saying that Cross-rail, Congestion charging, Low Emission Zone, and even parking meters shape traveler preferences.

Third, there is a social interest in influencing individual travel preferences towards being less environmentally damaging, less energy consuming, less congestion inducing, and less urban space demanding forms of travel. This may be a necessity given the mounting pressure of human activities on the natural resources that represent hard constraints.

Fourth, it is possible to retain the commitment to democracy and to discuss the appropriateness of traveler preferences because the democratic commitment is mainly procedural. There is not necessarily inconsistency between democracy and preference evaluation and reformation as long as the goals chosen to guide preference reformation are arrived at through a democratic process that includes public input and free exchange of information. We can come to a democratic consensus about our shared preferences for a sustainable society through a process of discussion and debate, and

then use these principles as guides to encourage people to see the inappropriateness of some preferences, given the scientifically demonstrable impacts of acting on those preferences. (Norton et al 1998)

Finally, the author will in this dissertation take the standpoint of "libertarian paternalism" as defended by Thaler and Sunstain (2003), which is an approach that preserves freedom of choice but authorizes both private and public institutions to steer people in directions that will promote their welfare.

Given the de facto existence and necessity of preference shaping, the correct question is not whether to shape traveler preferences, but how to implement it in a democratic way. More specifically, the questions include whether it is possible in a democratic society to bring scientific, rational, moral arguments to bear on the question of whether some sets of traveler preferences are more defensible than other sets; and whether it is possible to respect individual self determination of preferences and at the same time to address the possibility that sincerely felt preferences of many individuals will nevertheless be detrimental to society as a whole? (Norton et al 1998)

7.5.4 Practicality of preference shaping in transportation planning

The full discussion of how to implement preference shaping in transportation planning is beyond the scope of this dissertation. The author only points out a few directions in which transportation agencies may look.

(A) Learning from private marketing

Marketing has been a powerful tool used by private firms to influence consumer preferences. Despite the efforts and success of social marketing in areas such as anti-drug, anti-smoking, and anti-drunk-driving, the application of marketing by transportation agencies remains limited. There are experiences and techniques that the public sector can learn from private industry. A good example is the six weapons of influence identified by Cialdini (2001): reciprocation, commitment and consistency, social proof, authority, liking and scarcity.

(B) Behavior vs. economics in public policy

Amir et al (2005) noted that despite an extensive inventory of findings relevant to individual and market level anomalies, the behavioral literature on choice has had only a modest influence on regulatory action and policymaking. This contrasts sharply with the consideration given to traditional economic logic about the effects of price mechanisms and incentives in the design of regulatory interventions and social policy. Transportation agencies may improve this situation by broadening the domain of knowledge and embracing the implications of research findings from behavioral psychology.

(C) From all-or-nothing to a continuum of public intervention

There is a spectrum of levels of public intervention in influencing preference between full freedom and the complete prohibition. Public health, environmental protection, public security and climate change may require different intensities of intervention. Policy intervention in urban transportation requires careful thinking because of the complexity of travel behavior, which makes it useless to assess what travel modes are encouraged and what are not without the specific context of space and time. Therefore efforts to influence traveler preferences need to be localized and adaptive.

(D) Endogenous and exogenous influences

To what extent can we influence travel preferences? When discussing traveler preference changes, transportation agencies need to distinguish the influences from the societal trend from those actively pursued by the agencies. We don't want to overstate the scope of the behavioral change that could be achieved by active policy intervention on travel preferences. This is particularly important for project appraisal. For example, environmental attitudes have impact on travel behavior as identified by this dissertation, but recent changes in environmental attitudes are largely due to the social climate change campaign which is beyond transportation agencies' responsibility. However transportation agencies need to understand and take advantage of these

societal trends by actively connecting the urban transportation debates to the discussion on the environment and global warming.

(E) Open dialogue and careful scrutiny

Policies that aim to influence traveler preferences must be submitted to the most disciplined analysis and considered carefully on their merits. Calls for such policies to affect public values and change individual behaviors in service of a social agenda may be misused to manipulate opinion in service of narrower-than-public interests. Nor is there a foolproof way of separating justified public interventions on traveler preferences from unjustified ones. Any efforts to evaluate and shape travel preferences need to be done openly and based on dialogue and consensus. A stronger role for public discussion and participation is required so that the community processes will encourage articulation and evaluation of travel preferences and corresponding policy goals.

7.5.5 Application example: STDM in Sutton, London

London's *Smart Travel Demand Management* (STDM) programs provide an application example, where a campaign has been implemented by Transport for London to reduce car usage and encourage walking and cycling in Sutton, one of the 33 London boroughs. The campaign includes the personalized travel plan (PTP), workplace travel plan (WTP) and school travel plan (STP) programs, which provide education and information on the environmental, health and congestion costs of car use, the health benefits of walking and cycling, public transport options, and other livable community initiatives, but no financial incentives or changes to the transportation infrastructure. Surveys in 2006 (before) and 2007 (after) are documented for Sutton as the experiment and Croydon, a neighboring borough in London, used as a control area (Transport for London 2008).

Preliminary results show that STDM programs impacted four aspects of travel: awareness, attitude, intention and behavior, but the impacts on awareness, attitude and intention are more significant than those on behavior:

1) there are significant increases in people's awareness of local activities to do with changing travel behavior in Sutton compared to Croydon;

2) there are significant increases in positive attitudes toward public transport in Sutton compared to Croydon;

3) the proportion of residents who expressed an intention to reduce car use are significantly higher in Sutton than in Croydon;

4) the car mode share decreased in Sutton, but not significantly different from the decrease in Croydon; the average monthly mileage decreased significantly more in Sutton than in Croydon; school trips are where the car mode share decreased the most in Sutton in comparison to in Croydon.

The London STDM project is relatively young but the local community seems to be responding positively. The long-term effect of these campaigns to influence people's perceptions and preferences remains to be seen. In particular we need to examine whether the impact will be principally at the awareness, attitude and intention level or if it will finally materialize as meaningful and sustainable behavioral changes.

7.6 Limitations

There are a number of unresolved issues in this dissertation, including:

1. Specification of models with feedback loops (non-recursive models)

For example, in the model of environmental attitudes and car mode share in Chapter 4, the choice of the sets of variables that have direct effects on *f_Env*, *f_EnvGov* and *f_EnvTax* and ShCar is not fully justified. Many are based on rather weak intuitions.

2. Model with multiple latent classes

In the combined latent class and latent variable models, the dissertation only reported the results of models assuming two latent classes. When more than two latent classes

were attempted, none of the models reached the global maxima of the log likelihood function even after increasing the random starts of the optimization to 200.

3. R-square in non-recursive model

The typical R-square becomes meaningless in non-recursive models. Therefore this dissertation did not report R-square for models with feedback loops. Bentler-Raykov corrected R-square could be used for nonrecursive models as an alternative measure of the overall goodness-of-fit.

4. Not fully developed base model

Models that do not include latent variables are used as base models for comparison with models with latent variables. But many base models are not fully developed to include all the observed variables. For example, in the car ownership model, the base model does not include parking availability or congestion level, which are both important determining factors of car ownership. The consequences are twofold: first, if the omitted variables are correlated with the latent factors, this may result in biased estimates of the coefficients of the latent factors; second, the additional explanatory powers of the latent factors may be exaggerated since they are compared to the not fully developed base models.

7.7 Future research

There are two general directions for further investigation that are complementary to each other: on one hand, the applications of the existing innovations in incorporating traveler preferences into the transportation planning have yet to begin. On the other hand, the practical requirement to integrate travel preferences into transportation planning poses new challenges to research. Specifically five areas deserve attention for further research.

7.7.1 Fill in the matrix

If we draw a matrix with the factors of traveler preferences as rows, and the aspects of travel behavior as columns and fill in the cells with research that focus the relationships between a specific factor of preferences and a specific aspect of behavior, we will find the majority of the cells are empty.

An individual's travel decision can be generalized as a multi-stage process with long-term decisions such as residential location, work location, and car ownership; and short-term decisions such as choice of traveling or not, choice of travel mode, choice of departure time and choice of path. Travel preferences should be discussed with respect to each of these decision stages such as preference for residential location, preference for car ownership, preference for time allocation between travel and activities, preference for mode choice, etc. In all or some of these aspects of travel behavior, latent factors may play a role in influencing behavior. This is true for both the traditional four-step models and for the more recent activity-based models.

Examining the way the cells are first chosen to be filled, it is not surprising to find it is a compromise between what is important to study and what is easy to study. Researchers find whatever can be researched, selecting topics by doing our own benefit-cost analysis. Just as there is haphazardness in data collection on psychological factors, there is similar haphazardness in our research on the relationship with travel behavior. The lack of data and the lack of research reinforce each other. While this is natural and may be acceptable for any individual researcher, it can be a problem for the research community as a whole.

7.7.2 Identify the core

In a seemingly opposite direction from the previous point, a more important issue may be to identify the core sets of travel preferences. Reviewing the research on psychological factors, we can easily find over 20 factors that are related to travel behavior. It is unrealistic for transportation agencies to take on all of them and measure,

analyze and integrate them into transportation models. More seriously, transportation planners are often confused and overwhelmed by all these factors with fancy names, which are always infinitely intertwined and never defined in the same way. The decision to ignore all of them is not surprising given this confusion.

It is helpful to look at the observed attributes again: travel time and travel cost, simple and clear. Many will argue they are too simple to capture all the complexities of a transportation system. But the simplicity and clarity result in a powerful concentration of consistent effort to monitor, analyze and forecast these two factors. These are the core of the observed attributes. We need to identify the core of the latent factors as well.

7.7.3 Track the dynamics and prepare for forecasting

To observe and understand history is the first step toward forecasting the future. Macroeconomists have decades of data available to analyze before forecasting the economic future. Demographers have decades or even centuries of data to study before forecasting population changes. But we have not accumulated enough knowledge on the evolution of the latent factors of traveler preferences. More studies on latent factors of traveler preferences are based on cross-sectional rather than longitudinal data. No research has been able to track even five or ten years of consistent data on these latent factors. No wonder little theory has been developed to explain the underlying mechanism of their evolution.

7.7.4 Examine the triggers

Many triggers may influence traveler preferences, including personal ones and societal ones. The personal ones include things like changes of personal situation, e.g. getting married, having babies, growing older; and the changes of the sense of purposes and priorities associated with personal situations, e.g. more responsibility, less risk-aversion, and more relaxed.

The societal ones include reputational issues such as pride and self-esteem; social responsibility issues such as environmental and social equity concerns (either pure altruism or smug factor); life and work style issues such as more diversified activities increasing the complexity of scheduling and more women labor participation remixing household member responsibilities and shifting trip purposes and locations.

Technology can be another trigger. For example information and communication technology (ICT) innovations may increase people's expectations for transport service and therefore change people's perceptions of the services.

7.7.5 Standardize the practice

Without losing recognition of the diversity and dynamics of situations, transportation agencies and the research community should work together to establish standards for identifying and measuring the set of core latent factors that are found to be important in determining travel behavior and reasonably stable in their capacity to be quantified. The standards should include at least:

1) The selection of core factors, the definition of the factors and the set of indicators to measure them, and even specific wording for certain critical aspects of the questionnaires

2) The frequency and regularity of customer surveys and the spatial and demographic coverage

3) The basic analysis methodology and specific outputs including those that can be fed into the demand modeling team's quantitative tools

There is always a tradeoff between standardization and flexibility. The emphasis at particular times may alternate. Now it seems to be a time that a certain level of standardization will help.

7.8 Concluding remarks

Planners are synthesizers. We look across disciplines and integrate them according to the practical needs. We examine institutions and identify the problems and opportunities. We make tradeoffs between rigor and practicality and help bridge the gap between theory and practice. To incorporate traveler preferences into transportation planning demands a complex synthesis and careful tradeoffs.

Planners are also visionaries. When we envision the future, we make blueprints for transportation systems but this is only half the job. Traveler preferences should be part of the vision. If planning is the organization of hopes, traveler preferences are their embodiment in transportation.

The discussion on traveler preferences may be most relevant to the fast urbanizing countries such as China where fast urbanization is concurrent with fast motorization. Many Chinese households are as eager to get a car as western families. Given the population density, which is an order-of-magnitude higher than American cities, to have one car per family is physically impossible for Chinese cities. However, thanks to China's economic growth, it will not be too far in the future when an average Chinese family is able to afford a car. The association between travel mode with the social status manifestation is deeply rooted in Chinese tradition and people have already begun to associate public transportation and bicycling with being poor. If every Chinese strives to have a car as part of his/her successful life, no technical solutions are there yet to satisfy this desire.

What matters then is "what defines the ideal life". We need to examine questions such as “can we promote environmentally friendly travel modes and living patterns as part of Chinese ideal life in the face of dramatic urbanization?”. China is entering a critical stage of defining the life ideal, and how this ideal materializes in people’s living, working and traveling will have tremendous impacts on the society as a whole.

To incorporate traveler preferences into transportation planning may be a good-to-have add-on in the developed countries, but it seems to be a necessity in developing countries such as China.

Appendix A: Psychometric Indicators in the Londoner's Lifestyle and Car Dependence Survey

Table A-1: 80 statements on attitudes and personality traits

For each of the following 80 statements, please select one of the five responses:

- Agree completely
- Agree partially
- Neither
- Disagree partially
- Disagree completely

ID	Statement Description
A01	I am actively trying to use my car less
A02	I'm happy to pay more tax if the money is spent wisely
A03	It's OK to disobey the law if it doesn't make sense
A04	I consider speeding to be a crime
A05	I am an active member of the local community
A06	I regularly review my travel options
A07	Before making a car trip I look into whether I could use train or bus instead
A08	I don't have time to think about how I travel, I just get in my car and go
A09	You shouldn't force people to change in order to protect the environment
A10	I recycle most of my rubbish
A11	I don't have enough time to sort through my rubbish so it can be recycled
A12	Environmental concerns were a major factor in choosing the car I have
A13	I have looked into dual fuel cars and am interested in getting one the next time I change cars
A14	I'm very careful about how much water I use
A15	The government should take more of a lead in protecting the environment, even if people don't like it
A16	Being environmentally responsible is important to me
A17	Environmental threats such as global warming have been exaggerated
A18	People should be allowed to use their cars as much as they like, even if it causes damage to the environment
A19	For the sake of the environment, car users should pay higher taxes
A20	I would like to reduce my car use but there are no practical alternatives
A21	Driving my car is too convenient to give up for the sake of the environment
A22	Safety was a major factor in choosing my car
A23	Young children need to be accompanied by an adult when traveling to school
A24	Children should get into good habits by walking to school even if their parents don't like it

A25	**When shopping for food I spend a bit of time looking at nutritional information**
A26	**I go to the gym regularly**
A27	**I don't get as much exercise as I should**
A28	**Using the bus helps make you fitter**
A29	**I can't be trusted with a credit card!**
A30	**I am careful about money**
A31	**Before purchasing something I like to use the internet to find out the best option**
A32	**I treat filling up my car with petrol as part of the general weekly shop**
A33	**I'm very protective of my personal space**
A34	**I always plan things in advance**
A35	**I like to be in control**
A36	**I'd prefer to take part in a lottery with one prize of ?1m than 100 prizes of ?10,000**
A37	**I don't take part in the lottery and don't gamble**
A38	**I'm always on time**
A39	**I often act spontaneously**
A40	**I am someone who is prepared to take risks**
A41	**I often go out of my way to explore new places**
A42	**I'm often one of the first people to try out a new product**
A43	**I try to avoid the latest fads or crazes**
A44	**I regularly up-date my mobile phone so I have the latest version**
A45	**I drive because it's convenient and not because I enjoy it**
A46	**I like traveling by train because I can use the time constructively, such as by reading or working**
A47	**Driving gives me a feeling of being in control**
A48	**The bus services where I live are not good enough for me to want to use them**
A49	**I worry about who I might end up sitting next to on the bus or Tube**
A50	**I'm safer in my car than when using public transport**
A51	**Teenagers should be encouraged to use public transport rather than get a driving license**
A52	**Cars nowadays are very environmentally friendly**
A53	**I'm proud of my car**
A54	**I enjoy cycling**
A55	**Having a car gives me a great sense of freedom**
A56	**I'm happy to cycle, but only in good weather**
A57	**If there is a bus due every 15 minutes, I'd expect to have to wait at least 15 minutes at the bus stop**
A58	**If I'm traveling by train to a meeting I'll catch the train before the one I need in case there are delays**
A59	**Charging for road use on a "pay as you go" basis would make people more aware of the real costs of car travel**
A60	**If I'm driving to a meeting I'll allow extra time in case there is congestion**
A61	**Road congestion is something you just have to learn to live with**
A62	**I like travelling in a car**

A63	**I find car driving can be stressful sometimes**
A64	**Reducing my car use would make me feel good**
A65	**It would be easy for me to reduce my car use**
A66	**I would be willing to pay higher taxes on car use if I knew the revenue would be used to support public transport**
A67	**It is important to build more roads to reduce congestion**
A68	**Parking in my local town centre is easy**
A69	**I live a hectic life**
A70	**I like to work hard and play hard**
A71	**I go out most evenings**
A72	**I often escape to the country**
A73	**My lifestyle is dependent on having a car**
A74	**I have increased my use of bus over the last few years**
A75	**I am not interested in reducing my car use**
A76	**The car a person owns says a lot about the kind of person they are**
A77	**I only travel by bus when I have no other choice**
A78	**The more other people use public transport, the more I will**
A79	**I could not use public transport any more than I already do**
A80	**Reducing my car use will not make a difference to congestion because most other people will not reduce theirs**

Table A-2: 22 statements on perceptions

For each of the following 22 statements, please inform me of each form of transport (walking, cycling, bus, train, Tube, cars) where you agree with or associate the statement with that form. It doesn't matter whether or not you have ever used these methods of transport.

ID	Statement Description
QA1	**Ideal for unfamiliar journeys**
QA2	**A method of transport I would want to be seen using**
QA3	**Convenient to use**
QA4	**An unpleasant experience**
QA5	**Good value for money**
QA6	**Normally get you to your destination on time**
QA7	**Stressful**
QA8	**Easy to understand fare system**
QA9	**It is easy to buy tickets**
QA10	**Usually the best way to get round London**
QA11	**Generally reliable**

QA12	**Usually frequent**
QA13	**Provide easy to understand information**
QA14	**Well integrated with other transport**
QA15	**Are getting worse**
QA16	**Can get where you want to get to**
QA17	**This is a safe means of transport**
QA18	**Give up to the minute information**
QA19	**Used by people I am not comfortable with**
QA20	**Becoming more popular**
QA21	**Simple to use**
QA22	**I would be concerned for my personal security**

Appendix B: Speed Regression to Calculate the Travel Time for Alternative Travel Options

The travel time of the non-chosen alternatives is approximated by the average speed, which is determined by a regression model that differentiates speed by travel mode, trip distance, trip purpose, gender and age, time of day and location.

The travel modes include car driver, car passenger, walk, cycle, bus and train. The time of day includes early morning, AM peak, inter-peak, PM Peak, evening and night. The trip purposes include working, education, leisure, personally business, shopping and escorting children to school. Greater London is partitioned into 7 zones: Central, Inner North, Inner South, Outer North, Outer East, Outer South and Outer West. 29 OD pairs are constructed combining these origin and destination zones.

The regression is estimated based on LATS survey 2001, which has 176k records of trips with the detailed information of trip origin, destination, travel time, mode, purpose, and socioeconomics of the travelers. Table B-1 shows the results of the speed regression.

The regression results are then applied to the trips surveyed in the Londoners' Lifestyle and Car Dependency Survey to calculate the travel time for the non-chosen alternatives.

Table B-1 Results of the Speed Regression

Mode	Car Drivers		Car Passenger		Bus		Train		Cycle		Walk	
R2	0.566		0.537		0.484		0.583		0.467		0.268	
X	Beta	t	Beta	t	Beta	t	Beta	t	Beta	t	Beta	t
(Constant)	1.639	109.6	1.673	67.4	1.125	47.5	1.273	43.3	1.614	20.0	1.240	34.7
LnDistTotal	0.481	185.1	0.477	118.2	0.593	99.4	0.557	64.0	0.437	38.5	0.386	115.3
Education	-0.023	-1.3	-0.061	-5.4	-0.071	-6.5	-0.042	-3.0	-0.066	-2.0	-0.125	-16.0
Leisure	0.110	16.4	0.030	2.9	0.025	2.0	0.034	2.8	0.019	0.7	0.003	0.4
PrsnlBusi	0.102	11.5	0.008	0.6	0.043	2.9	0.101	5.1	-0.037	-0.9	0.009	0.9
Shopping	0.154	22.8	0.073	6.4	0.122	11.1	0.158	9.9	0.134	4.4	0.055	7.6
EducEscort	0.122	15.6										
EarlyAM	0.165	12.7	0.077	2.4	0.105	3.6	0.024	1.1	0.049	1.1	0.045	1.4
InterPeak	0.043	7.1	0.007	0.7	-0.005	-0.6	0.019	1.6	0.007	0.3	-0.003	-0.5
PMPeak	-0.041	-6.3	-0.016	-1.4	-0.054	-4.7	-0.026	-2.7	-0.016	-0.6	-0.003	-0.4
EVENING	0.136	15.8	0.130	9.8	0.051	2.8	0.033	2.1	-0.025	-0.7	0.054	4.7
NIGHT	0.178	14.0	0.146	8.3	0.049	2.0	-0.031	-1.3	0.019	0.3	0.038	2.2
Elder	-0.032	-4.9	-0.075	-7.5	0.001	0.1	-0.053	-3.0	-0.116	-3.3	-0.172	-23.2
Male	0.000	0.0	-0.030	-4.3	0.033	4.4	0.022	2.9	0.101	5.1	0.055	10.8
C-C	-0.223	-6.1	-0.211	-3.6	-0.026	-0.8	-0.023	-0.8	-0.195	-1.9	0.154	4.2
C-IN	-0.134	-6.0	-0.134	-3.8	-0.155	-6.3	-0.016	-0.7	-0.001	0.0	0.092	2.3
C-IS	-0.176	-6.0	-0.176	-3.4	-0.155	-5.7	-0.037	-1.5	-0.038	-0.4	0.138	2.7
C-OE	-0.113	-2.6	-0.175	-2.4	-0.079	-0.8	0.013	0.5	-0.066	-0.3	0.046	0.2
C-ON	-0.146	-4.5	-0.194	-3.4	-0.136	-3.0	0.008	0.3	-0.093	-0.7	0.100	1.8
C-OS	-0.129	-3.2	-0.161	-2.3	-0.112	-1.1	-0.008	-0.3	-0.227	-0.7	0.086	2.4
C-OW	-0.042	-1.1	-0.114	-1.8	-0.056	-0.4	-0.025	-0.9	-0.016	-0.1	-0.076	-1.0
GL-R	0.258	17.5	0.304	12.5	0.010	0.3	0.015	0.5	0.072	0.8	0.119	0.7
IN-IN	-0.055	-3.4	-0.005	-0.2	-0.087	-3.9	-0.056	-2.2	0.056	0.7	0.070	0.9
IN-IS	-0.199	-7.4	-0.225	-4.9	-0.090	-2.2	-0.061	-1.9	-0.057	-0.6	0.035	1.0
IN-OE	-0.043	-1.9	0.017	0.4	-0.133	-3.0	0.055	1.4	-0.323	-1.9	-0.066	-1.0
IN-OS	-0.195	-5.4	0.001	0.0	-0.040	-0.2	0.026	0.5	-0.003	0.0	n.a	
IN-OW	-0.037	-1.5	-0.014	-0.3	-0.116	-2.6	-0.001	0.0	-0.005	0.0	n.a	
IS-IS	0.018	1.1	0.042	1.6	-0.085	-3.7	-0.049	-1.4	-0.036	-0.4	n.a	
IS-OE	0.020	0.8	0.026	0.6	-0.096	-2.1	0.111	1.6	-0.051	-0.4	n.a	
IS-ON	-0.252	-4.0	-0.204	-2.3	n.a		-0.114	-1.5	n.a		n.a	
IS-OS	0.008	0.4	0.065	2.1	-0.088	-2.9	0.047	1.5	0.104	0.8	0.214	4.1
IS-OW	-0.078	-2.2	0.118	1.7	-0.164	-1.6	0.071	1.4	-0.015	-0.1	0.240	2.0
OE-OE	0.227	15.2	0.253	10.7	-0.018	-0.8	0.147	3.6	0.102	1.2	0.093	2.6
OE-ON	0.107	3.8	0.163	3.1	0.088	1.2	-0.074	-0.8	0.678	2.0	0.028	0.3
OE-OS	0.162	6.3	0.294	6.8	0.176	2.7	0.201	0.9	0.238	0.7	0.033	0.3
OE-OW	0.021	0.3	-0.181	-0.9	n.a		0.038	0.2	n.a		n.a	
ON-ON	0.150	9.7	0.179	7.2	-0.003	-0.1	0.020	0.5	-0.056	-0.6	0.047	1.3
ON-OS	-0.219	-3.1	-0.127	-0.8	n.a		0.456	2.5	n.a		n.a	
ON-OW	0.100	5.0	0.122	3.6	-0.107	-2.7	0.024	0.5	-0.182	-1.3	0.072	1.3
OS-OS	0.203	13.8	0.237	10.0	0.019	0.9	0.014	0.4	0.115	1.4	0.096	2.7
OS-OW	0.052	1.9	0.071	1.4	-0.003	-0.1	0.088	1.4	0.124	1.1	0.087	1.0
OWOW	0.156	10.6	0.199	8.3	-0.009	-0.4	0.098	3.0	0.093	1.2	0.092	2.6
R-R	0.336	22.8	0.372	15.5	0.059	1.9	-0.195	-3.1	0.072	0.9	0.066	1.8

Appendix C: Example Mplus Codes

C-1: Mplus Code for Model 5 in Chapter 5

```
TITLE:
    Model 2c5: Model Choice Model with Multiple Latent Factors in Hierarchical
Relationships

DATA:
    FILE IS LifestyleTrips.dat;

VARIABLE:
    NAMES ARE
                TripID    [...other variables omitted...] PTAL;
    Missing are All (-9999);
    USEVARIABLES are
                A33 A34 A35 A38 A58 A60
                A39 A42 A44    A69 A70 A71
                A10 A12 A13 A14 A16
                A02 A19 A59 A66
                QA1 QA3 QA16 QA21
                A47 A53 A55 A62
                Young Elder Male SGrade Cars HavBike
                Christ British Working Student Adult1  Adult3   HavChild
                TT_Bus TT_Train TT_Cycle TT_Walk TT_Pass TT_Drive
                OuterL D_Emp D_Pop Entropy PTAL
                PurWork PurEsco PurShop PurEdu PurLei PurPrnl
                TimeAM      TimeEve AccTrain
                ModeR;

    NOMINAL ARE ModeR;

DEFINE:
    ModeR = 7-Mode;
    !1: Walk, 2: Cycle; 3: Train, 4: Bus, 5: Car_Passener, 6: Car_Driver (reference)

    ! Define trip purpose dummies
    PurEsco = 0;
    If (purpose==1) THEN PurEsco=1;
    PurEdu = 0;
    If (purpose==2) THEN PurEdu=1;
    PurLei = 0;
    If (purpose==3) THEN PurLei=1;
```

```
PurPrnl = 0;
If (purpose==4) THEN PurPrnl=1;
PurShop = 0;
If (purpose==5) THEN PurShop=1;
PurWork = 0;
If (purpose==6) THEN PurWork=1;

! Define time of day dummies
TimeEAM = 0;
If (TimePeri==1) THEN TimeEAM=1;
TimeAM = 0;
If (TimePeri==2) THEN TimeAM=1;
TimeIP = 0;
If (TimePeri==3) THEN TimeIP=1;
TimePM = 0;
If (TimePeri==4) THEN TimePM=1;
TimeEve = 0;
If (TimePeri==5) THEN TimeEve=1;
TimeNigh = 0;
If (TimePeri==6) THEN TimeNigh=1;

! Define access to train station dummy
AccTrain = 0;
IF (DISTRAIL<=0.5 OR DISTTUBE<=0.5) THEN AccTrain=1;

SGRADE=7-SGRADE;
IncX=IncX/10000;
D_Pop=D_Pop/10000;
D_Emp =D_Emp /10000;
VMT = VMT / 1000;
PTAL=PTAL/10;
TT_Bus=TT_Bus/60;
TT_Train=TT_Train/60;
TT_Cycle=TT_Cycle/60;
TT_Walk=TT_Walk/60;
TT_Pass=TT_Pass/60;
TT_Drive=TT_Drive/60;
QA4=-QA4;
QA7=-QA7;
QA15=-QA15;
QA19=-QA19;
QA22=-QA22;
A09=-A09;
A17=-A17;
```

```
    A18=-A18;

ANALYSIS:
    ESTIMATOR = ML;
    INTEGRATION = MONTE (500);
    PROCESSORS = 4;

MODEL:
        ! Define latent variable measurement equations
            f_InCtrl BY A33 A34 A35 A38 A58 A60;
            f_Extro BY A39 A42 A44 A69 A70 A71;
            f_Env BY A10 A12 A13 A14 A16;
            f_Tax BY A02 A19 A59 A66;
            f_Conven BY QA1 QA3 QA16 QA21;
            f_CarLov BY A47 A53 A55 A62;

        ! Specify covariances among indicators
            A66 WITH A02;
            A14 WITH A10;
            A13 WITH A12;
            A44         WITH A42;
            A39         WITH A42;
            A70         WITH A69;
            A60         WITH A58;
            A39         WITH A34;
            A58         WITH A35;
            A38         WITH A34;
            A38         WITH A35;

        ! Specify the interrelationship among latent factors
            f_Env ON f_InCtrl;
            f_Tax ON f_Env;
            f_CarLov ON f_InCtrl f_extro f_Conven f_Tax;
            f_Conven ON f_tax;
            f_InCtrl WITH f_Extro;

        ! Specify the mode choice model
        ModeR ON Cars;
        ModeR#1 ON TT_Walk PurWork PurShop PurEdu PurLei PurPrnl
                    TimeAM HavBike Christ Working Adult1     OuterL Entropy
                    f_Conven f_CarLov;
        ModeR#1 ON TT_DRIVE (p2);

        ModeR#2 ON TT_Cycle PurWork PurEdu OuterL
```

```
                    f_Env f_Conven;
    ModeR#2 ON TT_DRIVE (p2);

    ModeR#3 ON TT_Train PurWork PurEdu PurLei
                    Young Elder    SGrade Christ
                    Student HavChild Adult1 Adult3 PTAL AccTrain
                     f_InCtrl f_Extro f_Env f_Conven f_CarLov;
    ModeR#3 ON TT_DRIVE (p2);

    ModeR#4 ON TT_Bus PurEsco PurEdu
                    Young Male    British Working Adult3
                     OuterL D_Emp D_Pop Entropy PTAL AccTrain
                     f_InCtrl f_Extro f_Conven f_CarLov;
    ModeR#4 ON TT_DRIVE (p2);

    ModeR#5 ON TT_Pass PurWork PurEsco PurLei TimeEve
                    Young Elder    Male Working
                    Adult1 Adult3 Entropy
                     f_Env f_Tax;
    ModeR#5 ON TT_DRIVE (p2);


OUTPUT:
    Tech1 SAMPSTAT PATTERNS STANDARDIZED ;

PLOT:
    TYPE IS PLOT3;
```

C-2: Excerpt of the Mplus Code for Model 3 Specification 3 in Chapter 6

```
TITLE:
    [lines omitted]
DATA:
    [lines omitted]
VARIABLE:
    [lines omitted]
    NOMINAL ARE CarsA;
```

```
DEFINE:
            CarsA = 3- CarsA;
            ! CarsA=1: Two Cars; CarsA=2: one car; CarsA=3: zero car;
    [lines omitted]
ANALYSIS:
    ESTIMATOR = ML;
    INTEGRATION = MONTE (500);
    PROCESSORS = 8;
MODEL:
        ! Define latent variable measurement equations
            f_Env BY A10 A12 A13 A14 A16;
            f_Tax BY A02 A19 A59 A66;
            f_Conven BY QA1 QA3 QA16 QA21;
            f_CarLov BY A47 A53 A55 A62;
        ! Specify covariances among indicators
            A66 WITH A02;
            A14 WITH A10;
            A13 WITH A12;
        ! Specify the structural equations for latent factors
                f_Env f_tax f_Conven f_CarLov ON
                    MALE Elder Young IncX SGrade
                    Working HavChild Adult1
                    D_Pop   PTAL OuterL AccTrain
                    CarTwo;
                f_CarLov ON SGrade@0;
        ! Specify the interrelationship among latent factors
            f_CarLov ON f_Conven f_Tax;
            f_Conven ON f_tax;
            f_Tax ON f_Env;
        ! Specify the car ownership model
            CarsA ON
                    MALE Elder IncX SGrade
                    British Working Student
                    HavChild Adult1  Adult3
                    D_Pop   Entrop    OuterL AccTrain
                    f_Tax f_Conven f_CarLov;
OUTPUT:
    TECH1 SAMPSTAT PATTERNS STANDARDIZED ;
PLOT:
    TYPE IS PLOT3;
```

C-3: Excerpt of the Mplus Code for Model 4 in Chapter 6

```
TITLE:
      [lines omitted]
DATA:
      [lines omitted]
VARIABLE:
      [lines omitted]
       CLASSES = c(2);
       NOMINAL ARE CarsA;
DEFINE:
       CarsA = 3- CarsA;
              ! CarsA=1: Two Cars; CarsA=2: one car; CarsA=3: zero car;
              ! CarsA#1: Two cars: CarsA#2=one car; CarsA#3= zero car;
      [lines omitted]
ANALYSIS:
      TYPE = MIXTURE;
      ESTIMATOR = ML;
       ALGORITHM=INTEGRATION;
       STARTS = 100, 7;
       PROCESSORS = 8;

MODEL:
         %OVERALL%    ! Definition for both classes
           ! Define latent variable measurement equations
                f_CarLov BY A47 A53 A55 A62;
           ! Define car ownership model
                CarsA ON Male-AccTrain f_CarLov;
           ! Define latent class membership model
                c ON Male-AccTrain;

         %C#1%            ! Definition for class 1
                CarsA ON f_CarLov;

OUTPUT:
      TECH1 SAMPSTAT PATTERNS STANDARDIZED ;
PLOT:
      TYPE IS PLOT3;
```

Bibliography

[1] Abou Zeid (2009) Measuring and Modeling Travel and Activity Well-Being, PhD Dissertation, Massachusetts Institute of Technology

[2] Adamowicz, W., Bunch, D., Cameron, T.A., Dellaert, B.G.C., Hanneman, M., Keane, M., Louviere, J. J., Meyer, R., Steenburgh, T., Swait, J. (2008) Behavioral Frontiers in Choice Modeling, Marketing Letters 19:215–228

[3] Allen, M. W. and S. H. Ng (1999) The direct and indirect influences of human values on product ownership, Journal of Economic Psychology 20 (1999) 5±39

[4] Allenby, G. M., & Lenk, P. J. (1994). Modeling household purchase behavior with logistic normal regression. Journal of the American Statistical Association, 89(428), 1218–1231.

[5] Allenby, G. M., & Lenk, P. J. (1995). Reassessing brand loyalty, price sensitivity, and merchandising effects on consumer brand choice. Journal of Business and Economic Statistics, 13(3), 281–289.

[6] Allenby, G.M.,&Rossi, P, E. (1999). Marketing models of consumer heterogeneity. Journal of Econometrics, 89, 57–78.

[7] Amir, O., D. Ariely, A. Cooke, D. Dunning, N. Epley, U. Gneezy, B. Koszegi, D. Lichtenstein, N. Mazar, S. Mullainathan, D. Prelec, E. Shafir, J. Silva. (2006) Psychology, Behavioral Economics, and Public Policy. Marketing Letters 16:3-4, 443-454

[8] Anable, J.; Lane, B.; Kelay, T. (2006). An evidence base review of public attitudes to climate change and transport behaviour. Final Report to the Department for Transport, July, London.

[9] Ajzen, I. (1991). The Theory of Planned Behavior. Organizational Behavior and Human Decision Processes, 50, 179-211.

[10] Ajzen, I. (2001). Nature and operation of attitudes. Annual Review of Psychology, 52, 27-58.

[11] Ashok, Kalidas, William R. Dillon and Sophie Yuan (2002) Extending Discrete Choice Models to Incorporate Attitudinal and Other Latent Variables, Journal of Marketing Research, 39(1), pp. 31-46

[12] Bamberg, S., Ajzen, I., & Schmidt, P. (2003). Choice of travel mode in the theory of planned behavior: The roles of past behavior, habit, and reasoned action.Basic and Applied Social Psychology, 25, 175-188.

[13] Ben-Akiva, M. (1973) Stucture of Travel Passenger Demand Models, Ph.D. Dissertation, Department of Civil and Environmental Engineering, Massachusetts Institute of Technology.

[14] Ben-Akiva, M. (1992) "Incorporation of Psychometric Data in Individual Choice Models". presented at the American Marketing Association Advanced Research Techniques Forum, Lake Tahoe, Nevada.

[15] Ben-Akiva, M. and B. Boccara (1987) "Integrated Framework for Travel Behavior Analysis". presented at the International Association of Travel Behavior Research (IATBR) Conference, Aix-en-Provence, France.

[16] Ben-Akiva, M. and B. Boccara (1995) "Discrete Choice Models with Latent Choice Sets". International Journal of Research in Marketing1 2. 9-24.

[17] Ben-Akiva, Moshe, Daniel McFadden, Kenneth Train, Joan Walker, Michel Bierlaire, Denis Bolduc, Axel B¨orsch-Supan, David Brownstone, David S. Bunch, Andrew Daly, Andre de Palma, Dinesh Gopinath, Anders Karlstrom, Marcela A. Munizaga (2002) Hybrid Choice Models: Progress and Challenges, Marketing Letters 13(3), 163-175.

[18] Ben-Akiva, M., Lerman, S., 1985. Discrete Choice Analysis: Theory and Application to Travel Demand, The MIT Press, Cambridge, Massachusetts.

[19] Ben Akiva, M., M. Bradley, T. Morikawa, J. Benjamin, T. Novak, H. Oppewal, and V. Rao (1994). ‘‘Combining Revealed and Stated Preferences Data,’’ Marketing Letters, 5(4), 335–350.

[20] Ben-Akiva, M. and T. Morikawa (1990) "Estimation of Travel Demand Models from Multiple Data Sources", Transportation and Traffic Theorvy4. 61-476.

[21] Ben-Akiva, M, Walker J, Bernardino A, Gopinath D, Morikawa T, Polydoropoulou A (2002) Integration of choice and latent variable models. In: Mahmassani H (ed) In Perpetual Motion: Travel Behaviour Research Opportunities and Application Challenges, Elsevier Science, 431-470.

[22] Bentler. P.M. (1980) "Multivariate Analysis with Latent Variables". Annual Review of Psychology 31, 419-456.

[23] Bentler, P.M., 1990. Comparative fit indexes in structural models. Psychometrika 107, 238–246.

[24] Bhat, C.R., 1997. An endogenous segmentation mode choice model with an application to intercity travel. Transportation Science 31, 34–48.

[25] Bhat, C. R. (2001). ‘‘Quasi-random Maximum Simulated Likelihood Estimation of the Mixed Multinomial Logit Model,’’ Transportation Research, vol 35B, pp. 677–693, August 2001.

[26] Bhat, C.R., and S. Castelar (2002). ‘‘A Unified Mixed Logit Framework for Modeling Revealed and Stated Preferences: Formulation and Application to Congestion Pricing Analysis in the San Francisco Bay Area,’’ Transportation Research, vol 36B, No. 7, pp. 593—616, August 2002.

[27] Bierlaire, M. (2003). BIOGEME: A free package for the estimation of discrete choice models , Proceedings of the 3rd Swiss Transportation Research Conference, Ascona, Switzerland.

[28] Blalock, H.M., 1961. Correlation and causality: the multivariate case. Social Forces 39, 246–251.

[29] Blalock, H.M., 1963. Making causal inferences for unmeasured variables from correlations among indicators.American Journal of Sociology 69, 53–62.

[30] Bollen, K.A., 1989. Structural Equations with Latent Variables. Wiley, New York.

[31] Boudon, R., 1965. A method of linear causal analysis: dependence analysis. American Sociological Review 30, 36 5–373.

[32] Bowles, Samuel (1998) Endogenous Preferences: The Cultural Consequences of Markets and Other Economic Institutions, Journal of Economic Literature 36: 75–111.

[33] Bradley Flamm 2009, The impacts of environmental knowledge and attitudes on vehicle ownership and use, Transportation Research Part D: Transport and Environment 14(4), pp 272-279

[34] Browne, M.W., 1984. Asymptotic distribution free methods in analysis of covariance structures. British Journal of Mathematical and Statistical Psychology 37, 62–83.

[35] Browne, M.W. (2001). An overview of analytic rotation in exploratory factor analysis. Multivariate Behavioral Research, 36, 111-150.

[36] Brownstone, D., Bunch, D. S., and Train, K. (2000). ‘‘Joint Mixed Logit Models of Stated and Revealed Preferences for Alternative-fuel Vehicles,’’ Transportation Research B, 34(5), 315–338.

[37] Browne, M.W., Cudeck, R., 1992. Alternative ways of assessing model fit. Sociological Methods and Research 21, 230–258.

[38] Bunch, D.S., 2000. Automobile demand and type choice. In: Hensher, D.A., Button, K.J. (Eds.), Handbook of Transport Modelling. Elsevier, pp. 463–479.

[39] Byrne, B.M., 2001. Structural Equation Modeling with AMOS: Basic Concepts, Applications, and Programming.Lawrence Erlbaum Associates, Hillsdale, NJ.

[40] Caflisch, R. E., Monte Carlo and quasi-Monte Carlo methods, Acta Numerica vol. 7, Cambridge University Press, 1998, pp. 1-49.

[41] Carroll, J.D. and P.E. Green (1995) "Psychometric Methods in Marketing Research. 1. Conjoint Analysis", Journal of Marketing Research 32(4), 385-391.

[42] Choo, S., Mokhtarian, P.L., 2004. What type of vehicle do people drive. The role of attitude and lifestyle in influencing vehicle type choice. Transportation Research Part A 38, 201–222.

[43] Choocharukul, K. Van, H.T. Fujii, S. (2008) Psychological effects of travel behavior on preference of residential location choice, Transportation Research A, 42 (1), pp. 116–124.

[44] Cialdini, R. B. (2001). Influence: Science and practice (4th ed.). Boston: Allyn & Bacon

[45] Colin Clark 1957 Transport-Maker and Breaker of Cities, Town Planning Rev., Vol. 28, pp. 236-250

[46] Cudeck, R., du Toit, S., S€orbom, D. (Eds.), 2001. Structural Equation Modeling: Present and Future. Scientific Software International, Chicago.

[47] Dobson, R., Dunbar, F., Smith, C.J., Reibstein, D., Lovelock, C., 1978. Structural models for the analysis of traveler attitude–behavior relationships. Transportation 7, 351–363.

[48] David Begg (2003), Congestion charging - the new realities, PUBLIC SERVICE REVIEW: TRANSPORT - SPRING 2003

[49] Dargay, J.M., Hanly, M., 2007. Volatility of car ownership, commuting and mode and time in the UK. Transportation Research Part A 41 (2007) 934–948

[50] De Jong, G. et al., 2004. Comparison of car ownership models. Transport Reviews 24, 379–408.

[51] Department for Transport, UK (2008). Public attitudes to climate change and the impact of transport. Department for Transport, London. Available online as at 10/06/08):

http://www.dft.gov.uk/pgr/statistics/datatablespublications/trsnstatsatt/atttoclimchangemay2008

[52] Dillon, W.R., and Kumar, A. (1994). Latent structure and other mixture models in marketing: An integrative survey and overview, chapter 9 in R.P. Bagozzi (ed.), Advanced methods of Marketing Research, 352-388,Cambridge: Blackwell Publishers.

[53] Duncan, O.D., 1966. Path analysis: sociological examples. American Journal of Sociology 72, 1–16.

[54] Finch, J.F., West, S.G., MacKinnon, D., 1997. Effects of sample size and nonnormality on the estimation of mediated effects in latent variables models. Structural Equation Modeling 4, 87–107.

[55] Garrett, M and B. Taylor (1999) “Reconsidering social equity in public transit”, Berkeley Planning Journal v13, p6-27

[56] Gardner and Abraham, 2007, What drives car use? A grounded theory analysis of commuters’ reasons for driving, Transportation Research Part F: Traffic Psychology and Behaviour 10 (3) (2007), pp. 187–200.

[57] Garling, T.. T. Laitila and K. Westin. Eds. (1998) Theoretical Foundations of Travel Choice Modeling, Elseveier Science. New York.

[58] Garling, T and P. Loukopoulos (2008) “economic and psychological determinants of car ownership and use”, The cambridge handbook of psychology and economic behaviour, edited by Alan Lewis, Cambridge University Press

[59] Giuliano, G.J., Dargay, J., 2006. Car Ownership, travel and land use: a comparison of the US and Great Britain. Transportation Research Part A 40, 106–124.

[60] Golob, T.F., A.D. Horowitz, and M. Wachs. "Attitude-Behavior Relationships in Travel Demand Modeling," in D.A. Hensher and P.R. Stopher, eds., Behavioral Travel Modeling , London: Croom Helm, Ltd. (1979), pp. 739-757.

[61] Golob, T.F., Hensher, D.A., 1998. Greenhouse gas emissions and Australian commuters’ attitudes and behaviour concerning abatement policies and personal involvement. Transportation Research D 3, 1–18.

[62] Golob, T.F., 2001. Joint models of attitudes and behavior in evaluation of the San Diego I-15 Congestion Pricing Project. Transportation Research A 35, 495–514.

[63] Golob, T.F. (2003). Structural equation modeling for travel behavior research. Transportation Research, Part B - Methodological, 37:1-25.

[64] Gopinath, A.D. (1995). Modeling Heterogeneity in Discrete Choice Processes: Application to Travel Demand. Ph.D. Thesis, Department of Civil and Environmental Engineering, Massachusetts Institute of Technology.

[65] Gorsuch, Richard L. (1983) Factor Analysis. Hillsdale, NJ: Erlbaum

[66] Grava, S (2002) Urban Transportation Systems: choices for communities, McGraw-Hill Professional

[67] Greater London Authority (2007), Action Today to Protect Tomorrow: The Mayor’s Climate Change Action Plan

[68] Greene, W. H. and Hensher, D. A. (2003), “A latent class model for discrete choice analysis: contrasts with mixed logit”. Transportation Research Part B 37: 681-698.

[69] Hall, P (2007) “Beyond the automobile”, Access, 30, p10-15

[70] Hanley G.P, Iwata B.A, Roscoe E.M. Some Determinants of Changes in Preference Over Time. Journal of Applied Behavior Analysis. 2006; 39: 189–202.

[71] Hausman, J. and D. Wise, “A Conditional Probit Model for Qualitative Choice: Discrete Decisions Recognizing Interdependence and Heterogeneous Preferences,” Econometrica, 1978, 46 (2), 403–426.

[72] Heckman, J. J. (1981): Statistical Models for Discrete Panel Data, in C. F. Manski and D. McFadden (ed) Structural Analysis of Discrete Panel Data with Econometric Applications, Cambridge, MA: MIT Press.

[73] Hensher, D. A, Greene W H, 2003, "Mixed logit models: state of practice" Transportation 30 133 – 176

[74] Honore, Bo E. and Ekaterini Kyriazidou (2000) Panel Data Discrete Choice Models with Lagged Dependent Variables, Econometrica, Vol. 68, No. 4, pp. 839-874

[75] Hu, L., Bentler, P.M., 1999. Cutoff criteria for fit indexes in covariance structure analysis: conventional criteria versus new alternatives. Structural Equation Modeling 6, 1–55.

[76] Ibrahim, M.F. (2003) Car ownership and attitudes towards transport modes for shopping purposes in Singapore, Transportation 30 (4) pp 435-457

[77] Jakobsson, C., Fujii, S., Garling, T., 2000. Determinants of private car users’ acceptance of road pricing. Transport Policy 7, 153–158.

[78] Joreskog, K.G., 1969. A general approach to confirmatory maximum likelihood factor analysis. Psychometrika 34,183–202.

[79] Joreskog, K.G., 1970. A general method for analysis of covariance structures. Biometrika 57, 239–251.

[80] Joreskog, K.G. (1973) "A General Method for Estimating a Linear Structural Equation System", Structural Models in the Social Sciences. A.S. Goldberger and O.D. Duncan, Eds., Academic Press, New York.

[81] Joreskog, K.G., 1990. New developments in LISREL—Analysis of ordinal variables using polychoric correlations and weighted least squares. Quality and Quantity 24, 387–404.

[82] Kahneman, D. 2003. A psychological perspective on economics. American Economic Review, 93: 162–168.

[83] Kahneman, Daniel and Snell, Jackie. (1992) “Predicting a Changing Taste.” Journal of Behavioral Decision Making, July 1992, 5(3), pp. 187– 200.

[84] Kaplan, D., 2000. Structural Equation Modeling: Foundations and Extensions. Sage Publications, Newbury Park, CA.

[85] Keane, M. (1997). Modeling heterogeneity and state dependence in consumer choice behavior. Journal of Business and Economic Statistics, 15(3), 310–327.

[86] Keesling, J.W., 1972. Maximum likelihood approaches to causal analysis. Ph.D. dissertation, Department of Education, University of Chicago

[87] Kitamura, R., 1989. A causal analysis of car ownership and transit use. Transportation 16 (2), 155–173.

[88] Kitamura, R., Bunch, D.S., 1990. Heterogeneity and state dependence in household car ownership: a panel analysis using ordered response models with error components. In: Koshi, M. (Ed.), Transportation and Traffic Theory. Elsevier, pp. 477–496.

[89] Kitamura, Ryuichi and Yusak O. Susilo (2005) Is Travel Demand Insatiable? A Study of Changes in Structural Relationships Underlying Travel. Transportmetrica 1 (1), 23 – 45

[90] Kline, R., Principles and Practice of Structural Equation Modeling, 2nd Edition

[91] Lachaab, Mohamed, Asim Ansari, Kamel Jedidi, and Abdelwahed Trabelsi (2006), Modeling Preference Evolution in Discrete Choice Models: A Bayesian State Space Approach, Quantitative Marketing and Economics, 4 (1), 57–81.

[92] Loewenstein, George and Adler, Daniel. 1995 “A Bias in the Prediction of Tastes.” Economic Journal, 105(431), Pp. 929–37.

[93] Loewenstein, G. (2001). The Creative Destruction of Decision Research. Journal of Consumer Research, 28 (3), 499–505

[94] Luce, R.D. and J.W. Tukey (1964) "Simultaneous Conjoint Measurement: A New Type of Fundamental Measurement", Journal of Mathematical Psychology 1. 1-27.

[95] MacCallum, R.C., Browne, M.W., Sugawara, H.M., 1996. Power analysis and determination of sample size for covariance structure modeling. Psychological Methods 1, 130–149.

[96] Manski, C. 1977 The Structure of Random Utility Models. Theory and Decision 8, pp229-254.

[97] Manski,C. & S. Lerman (1977), “The Estimation of Choice Probabilities from Choice Based Samples,” ECONOMETRICA; 45, 1977-88.

[98] Matas, Anna & Raymond, Josep-LLuis, 2008."Changes in the structure of car ownership in Spain," Transportation Research Part A: Policy and Practice, Elsevier, vol. 42(1), pages 186-202, January.

[99] McFadden, D., 1973, “Conditional Logit Analysis of Qualitative Choice Behavior,” in P. Zarembka, ed., Frontiers in Econometrics, Academic Press: New York.

[100] McFadden, D. (1984) "Econometric Analysis of Qualitative Response Models". Handbook of Econometrics II, Z. Friliches and M.D. Intriligator. Eds., Elsevier Science Publishers.

[101] McFadden, D. 1999 “Rationality for Economists?” Journal of Risk and Uncertainty, 19(1–3), Pp. 73–105.

[102] McFadden, Daniel. 2001. Economic choices. American Economic Review 91: 351–370.

[103] McFadden, D. (1986), 'The Choice Theory Approach to Marketing Research," Marketing Science, 5 (4), 274-97.

[104] McFadden, D. (2000) "Disaggregate Behavioral Travel Demand's RUM Side: A 30-Year Retrospective", presented at the International Association of Travel Behavior Research (IATBR) Conference, Gold Coast, Queensland, Australia.

[105] McFadden, D, 2001. "Economic Choices," American Economic Review, AmericanEconomic Association, vol. 91(3), pages 351-378

[106] McLachlan, G. and D. Peel, Finite Mixture Models. New York: John Wiley&Sons, 2000.

[107] Morikawa, T., Sasaki, K., 1998. Discrete choice models with latent variables using subjective data. In: Ortuzar, J.de.D.,Hensher, D.A., Jara-Diaz, S. (Eds.), Travel Behaviour Research: Updating the State of Pla. Pergamon, Oxford,pp. 435–455.

[108] Morrison, Donald F. (1990) Multivariate Statistical Methods. New York: McGraw-Hill.

[109] Mueller, R., 1997. Structural equation modeling: back to basics. Structural Equation Modeling 4, 353–369.

[110] Muthén, B. (2002). Beyond SEM: General latent variable modeling. Behaviormetrika, 29, 81-117.

[111] Muthen, Linda and Bengt Muthen (1998-2007): Mplus User's Guide. 5th Ed, Muthen & Muthen: Los Angeles.

[112] Noam Chomsky (2008). The election, the economy, and the world, public presentation in Boston

[113] Norton, B., Costanza, R., Bishop, R., 1998. The evolution of preferences: why 'sovereign' preferences may not lead to sustainable policies and what to do about it. Ecological Economics 24, 193–211.

[114] Nilsson and Küller, 2000 M. Nilsson and R. Küller, Travel behaviour and environmental concern, Transportation Research Part D 5 (2000), pp. 211–234.

[115] Olsaretti, Serena (Ed.) 2006: Preferences and Well-Being. Royal Institute of Philosophy Supplement: 59 Cambridge: Cambridge University Press.

[116] Ory, D. and P.L. Mokhtarian (2009) "Modeling the Structural Relationships among Short Distance Travel Amounts, Perceptions, Affections, and Desires", Transportation Research Part A. 43(1) Pages 26-43

[117] Payne, John W., James R. Bettman, and David A. Schkade. (1999). "Measuring Constructed Preferences: Towards a Building Code." Journal of Risk and Uncertainty 19, 243–270.

[118] Pendyala, R.M., Kostyniuk, L.P., Goulias, K.G., 1995. A repeated cross-sectional evaluation of car ownership. Transportation 22, 165–184.

[119] Prelec, D. 1991, Values and Principles: Some Limitations on Traditional Economic Analysis. In A. Etzinoi & P. Lawrence (eds) Perspectives on Socioeconomics. London: M.E. Sharpe

[120] Prevedouros, P.D., 1992. Associations of personality characteristics with transport behavior and residence location decisions, Transportation Research Part A: Policy and Practice, Elsevier, vol. 26(5), pages 381-391.

[121] Priemus H, 1995, "Reduction of car use: instruments of national and local policies—a Dutch perspective" Environment and Planning B: Planning and Design 22(6) 721 – 737

[122] Rabin, Matthew. (1998). "Psychology and Economics," Joumal of Economic Literature 36, 11-46.

[123] Randall, A., 1988. What mainstream economists have to say about the value of biodiversity. In: Wilson, E.O. (Ed.), Biodiversity National Academy Press, Washington, DC.

[124] Roy, R., Chintagunta, P. K., & Haldar, S. (1996). A framework for investigating habits, the hand of the past and heterogeneity in dynamic brand choice. Marketing Science, 15(3), 280–299.

[125] Saleh, Wafaa and Farrell, S (2007) Investigation and analysis of evidence of asymmetric churn in travel demand models. Transportation Research, Part A: Policy and Practice, 41 . pp. 691-702

[126] Sandqvist, 1997 Sandqvist, K. (1997). The appeal of automobiles—human desires and the proliferation of cars. KFB Rapport 1997:21. Stockholm, Sweden: KFB.

[127] Seetharaman, P. B. (2003). Modeling multiple sources of state dependence in random utility models of brand choice: A distributed lag approach. Marketing Science, 23(2), pp. 262-271

[128] Simon, Herbert. (1956) Rational Choice and the Structure of the Environment. Psychological Review, 63(2), Pp. 129-38.

[129] Simon, Herbert. (1955) A Behavioral Model of Rational Choice. The Quarterly Journal of Economics, Vol. 69, No. 1., pp. 99-118

[130] Simon, Herbert. 1990. Invariance of Human Behavior. Annual review of Psychology 41, 1-19.

[131] Slovic, Paul. (1995). "The Construction of Preference," American Psychologist 50, 364-371.

[132] Stanovich, K. E. & Richard F. West (2000) Individual Differences in Reasoning: Implications for the Rationality Debate? Behavioral and Brain Sciences 23 (5): 645-665

[133] Steiger, J.H., 1990. Structural model evaluation and modification: an interval estimation approach. Multivariate Behavioral Research 25, 173–180.

[134] Steiger, J.H., Lind, J.C., 1980. Statistically based tests for the number of common factors. Presented at the Annual Meeting of the Psychometric Society, Iowa City, IA.

[135] Swait, J., 1994. A structural equation model of latent segmentation and product choice for cross-sectional revealed preference choice data. Journal of Retail and Consumer Services 1 (2), 77–89.

[136] Temme, Dirk, Paulssen, Marcel and Dannewald, Till (2008) Incorporating Latent Variables into Discrete Choice Models - A Simultaneous Estimation Approach Using SEM Software (December 2008). BuR Business Research Journal, 1 (2): 220-237.

[137] Tversky, A. and D. Kahneman. (1981). “The Framing of Decisions and the Psychology of Choice,” Science 211(4481), 453–458.

[138] Tversky, A., Sattath, S., Slovic, P., (1988). Contingent weighting in judgment and choice. Psychol. Rev. 85, 371–384.

[139] Tversky, A., Slovic, P., Kahneman, D., 1990. The causes of preference reversal. Am. Econ. Rev. 80, 204–217.

[140] Thaler, Richard H. and Sunstein, Cass R. (2003) “Libertarian Paternalism.” American Economic Review, 93(2), Pp. 175–79.

[141] Transport for London 2003, Measuring Public Transport Accessibility Levels (PTALs)

[142] Transport for London 2003, London Area Travel Survey (LATS) 2001

[143] Transport for London (2003), Central London Congestion Charge, Social impacts Survey 2002, 2003

[144] Transport for London (2005a), LTS Technical Report TR01, B5.x Technical Summary, prepared by MVA for TfL and dated November 2005

[145] Transport for London (2005b), Railplan Modelling User Guide

[146] Transport for London (2006), Transport 2025: transport vision for a growing world city (T2025)

[147] Transport for London (2006), Londoners' Lifestyle and Car Dependence Survey

[148] Transport for London (2006), Reflecting Soft TDM Impact in LTS

[149] Transport for London (2007), Congestion Charging Impacts Monitoring - Fifth Annual Report

[150] Transport for London (2008), Smarter Travel Sutton, First Annual Report, March 2008

[151] Train, Kenneth E. 2003 Discrete Choice Methods with Simulation, Cambridge University Press

[152] UK Department for Transport, 2003. Transport Statistics Great Britain. HMSO, London

[153] UK National Centre for Social Research, 1993 and 1996, British Social Attitudes annual reports, SAGE Publications Ltd

[154] Vredin Johansson, M., Tobias Heldt, and Per Johansson (2006): The effects of attitudes and personality traits on mode choice, Transportation Research Part A: Policy and Practice, 40 (6): 507–525.

[155] Walker JL (2001) Extended discrete choice models: integrated framework, flexible error structures, and latent variables. Ph.D. dissertation, Massachusetts Institute of Technology.

[156] Walker, Joan and Li (2007) Latent Lifestyle Preferences and Household Location Decisions, Journal of Geographical Systems, (2007) 9:77–101

[157] Walker, Joan and Moshe Ben-Akiva (2002) "Generalized Random Utility Model", Mathematical Social Sciences 43(3), 303-343.

[158] Wedel, M., and Kamakura, W.A. (1998). Market segmentation: Concepts and methodological foundations. Boston: Kluwer Academic Publishers.

[159] Weinzierl, S. "Introduction to Monte Carlo Methods." 23 Jun 2000. http://arxiv.org/abs/hep-ph/0006269/.

[160] Whelan, G., 2007. Modelling car ownership in Great Britain. Transportation Research Part A 41, 205–219.

[161] Wiley, D.E. (1973) "The Identification Problem for Structural Equation Models with Unmeasured Variables". Structural Models in the Social Sciences, A.S. Goldberger and O.D. Duncan, Eds., Academic Press, New York.

[162] Wright, S., 1934. The method of path coefficients. Annals of Mathematical Studies 5, 161–215.