The effects of environmentalism and attitudes toward physical activity on travel behaviors

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Abstract

Traveling is one among human daily activities, and mobility has become a fundamental aspect of life. To date, the automobile industry and technologies have made it much easier for people to travel, from lower cost of owning a car to cheaper traveling by car sharing. The concept of travel footprint becomes relevant to this context: the more people travel, the more energy we consume and the more emissions we bear. Mass transit is clearly an intuitive solution, nevertheless people view this solution differently. For example, the travelers may want to satisfy their (unlimited) demands and, thus, preferring car use. The policymakers, on the other hand, concern how to keep travel footprints controllable for their environmental purposes. This dissertation takes the policymaker view in seeking for solutions of attracting travelers to public transport (PT). We are particularly inspired by the idea of (1): Triggering the traveler's norms to behave more pro-environmentally, i.e. using PT instead of private cars and; (2): Promoting PT uses by focus on their health benefits (e.g., more intakes of physical activities than car uses).

Specifically, we attempted to examine the effects of environmentalism and Attitudes toward Physical Activity (APA) on several travel behaviors. We are motivated by the potentials of intervening these general attitudes in shaping travel mode uses toward sustainability, i.e. more PT uses and less private car uses. We set three explicit objectives in this dissertation, including a proposal for combined policies, a suggestion for expanding the list of determinants for travel behaviors, and some methodological improvements. To facilitate these objectives, we followed basically three steps, including a literature review step, a framework development step, and an analysis step. Four cases studies were carried out in the last step using two data sets.

Our works initiated with understandings on the concept of attitude. We then explored various ways that attitudes diffuse over behavioral intentions and overt behaviors. From the literature reviewed, we designated the 'Motivation and Opportunity to serve as the major Determinants' (MODE) model and the Theory of Planned Behavior (TPB) as the theoretical bases for our postulation on the effects of environmentalism and APA on travel behaviors. Considering the popularity of some theoretical models, we designated a choice model framework and a Structural Equation Model (SEM) framework for examining the postulated effects. We introduced several logit-based choice models that can be used with mode choice data, and a standard SEM following a three-steps approach: a principal component analysis, a confirmatory factor analysis, and a full SEM, that is applicable to behavioral data.

The choice model framework and SEM framework were applied using two data sets. The first data set was obtained through a mobility management conducted in Asuke, a small rural town in Japan. Asuke is a low densely populated area where PT system includes only community bus and school bus with low frequencies. Data from Asuke were used with expectation that an established effects of APA on bus uses and bus use intentions would support policies in promoting for bus use by means of intervening on the factor APA. In contrast, the second data set was obtained by an online survey conducted in Nagoya city, Japan in 2018. Nagoya is a highly populated city with full public transport facility, and the data set collected in Nagoya includes only car drivers. This sample allowed for testing the effects of environmentalism and APA on mode choice behaviors and car use behaviors. The corresponding findings thus can contribute to efforts in promoting for public/active transport and for car use reduction.

We conducted four case studies with three forms of travel behaviors investigated, including travel mode choice behaviors, car use behaviors, and bus use intentions.

First, we tested the effects of environmentalism and APA on mode choice behaviors in the case study in **Chapter 4**. The data set collected in Nagoya was used including 821 respondents with 1840 reported trips. The Integrated Choice and Latent Variable (ICLV) model and Latent Class Choice (LCC) model were employed, followed by sensitivity and validity analyses. In the estimation results of the ICLV model where environmentalism was allowed to directly affect railway utility, and APA was modeled to cause bicycle and walking utility, only the effect of APA on walking utility was found being significant. The LCC model found a significant negative effect of environmentalism on the probabilities of being in Class 1 (e.g., pro-physical activity group) relative to Class 2 (e.g., pro-environmental group), and a significant positive effect of APA on the probabilities of being in Class 1 versus Class 2. This study thus confirmed the effect of environmentalism on the choices of rail and the effects of APA on the utilities/choices of walking, bicycle. In addition, the LCC model framework was found being useful in heterogeneity treatments in mode choice models with latent variables. Finally, this study revealed that cares for private benefits were higher than cares for environmental issues.

The result of the case study in Chapter 4 was supported by the result from the case study in **Chapter 5**. We tested the effect of APA on bus utility in a binary logit mode choice model between car and bus. The Asuke data set was used for estimating two postulated models, a clinic/hospital trips model of a sample consisted of 591 trips, and a shopping trips model with 734 trips, both in the Asuke sample. The analytic data were highly unbalanced. As a result, we embedded the Firth bias correction method into the model estimations. We found significant (indirect) effect of APA on bus utility for both cases with and without the bias correction method. In the case without the Firth method, we found very large standard errors in the estimates of some parameters. These errors, however, were reduced significantly when the Firth method was applied. This study thus confirmed the effect of APA on mode choice and signified the usefulness of Firth method in rare choice data.

In the case study in **Chapter 6**, car use behavior was of our interest. We tested several SEMs that allowed for reciprocal relationships and correlated error terms. The analytic sample included 900 respondents in the Nagoya data set. We employed chi-square difference tests to identify the best models from the postulated models, from that we could make hypothesis inferences. Three main findings were derived. First, unobserved determinants of environmentalism and car use accounted for more than 85% of their variances. Second, we found a significant negative correlation between environmentalism and car use. Finally, a significant causal effect from car use to environmentalism was found, but not in the opposite direction (e.g., from environmentalism to car use). This study thus confirmed that the relationship between environmentalism and car use behavior is mainly due to correlation, and that car use reduction policies should focus on factors other than environmentalism. This study has illustrated the importance of allowing various types of relationship, i.e. the best models could not be identified without allowing for reciprocal relationships and correlated latent variables.

In the case study in **Chapter 7**, the low bus share in Asuke motivated us in examining Bus Use Intention (BUI) as an immediate determinant of bus use. We postulated that APA can be linked to BUI as bus use includes certain physical activities. To test this assumption, we based on TPB in assuming that APA causes BUI indirectly through its effect on TPB mediators. This was operationalized by using SEMs and an additional multiple-group analysis. The analytic sample consisted of 1604 respondents was extracted from the Asuke data set. Overall, we found significant effects of APA on BUI in both direct and indirect way. However, the TPB mediators helped to observe these effect clearer and improved the model ability in accounting for the variance of BUI. Further, the effects were stronger for certain groups, such as young people, employed people, and car users. Thus, this study provided an empirical evidence for the hypothesis that APA causes BUI.

Overall, the four case studies converged on the same finding that environmentalism and APA have certain effects on travel behaviors. Policymakers, thus, can see this finding as a suggestion for combining transport policies with environmental and health policies as a cost-effective solution. For the literature in transport studies, we suggested environmentalism and APA as determinants of travel behaviors, and we expect that future studies will give more interests in these factors.

Keywords: Revised NEP scale; New Ecological paradigm; Attitude toward physical activity; Travel behavior; Data separation; Mode choice model; Theory of planned behavior; The MODE model.

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APA	Attitude toward Physical Activity	
BI	Bicycle	
BUI	Bus Use Intentions	
CFA	Confirmatory Factor Analysis	A covariance based technique for confirming the validity and reliability of a measurement model.
DA	Driver alone	
DCM	Discrete Choice Model	A choice model where the alternatives are distinguishable and there is no overlap between alternatives.
ICLV	Integrated Choice and Latent Variable	An ICLV model is a choice model where latent variables are integrated into the utility functions.
LCC	Latent Class Choice	A LCC model is a choice model where the individuals are segmented into latent classes that have different taste parameters.
LRI	Likelihood Ratio Index	A measure for evaluating the goodness-of-fit of choice models, calculated by one minus the ratio of the final log-likelihood over the log-likelihood of the model without parameters.
MLE	Maximum Likelihood Estimation	An estimation method for parametric models where the parameters are obtained by maximizing the likelihood of observing the data.
MM	Mobility Management	A strategy for modal shifts that is featured by the use of information and educational interventions.
MODE	Motivation and Opportunity to serve as the major Determinants	A behavioral model proposing that people may engage in a deliberate decision making process instead of a simultaneous decision making process if they have motivations to follow and the opportunity to follow exists.
NEP	New Environmental Paradigm	A scale for measuring environmental attitudes with focus on some new ways of thinking about the environmental issues. An extended version of this scale is termed as New Ecological Paradigm, or the revised NEP, featuring by adding ecological aspects of environmental issues to the original scale.
PBC	Perceived Behavioral Controls	
PCA	Principal Component Analysis	A statistical technique that allows data summarization by identify principal components.
PMS	Predicted Mode Shares	The mode shares predicted by the mode choice models using the estimated

		parameters and the observed traveler's characteristics and mode attributes.
PB	Public Transport	
RAIL	Railway	
RUM	Random Utility Maximization	A theory stating that each alternative has a random utility and the chosen one is the one with the largest utility
SEM	Structural Equation Model	A mathematical model that is based on covariance techniques. Basically, SEMs include a structural model, where latent variables are related, and a measurement model that shows how these latent variables are measured.
SN	Subjective Norms	
TPB	Theory of Planned Behavior	An extended version of TRA that adds perceived behavioral controls to the list of determinants of intentions and of behaviors
TRA	Theory of Reasoned Action	A behavioral theory with the central idea that reasoned actions develop directly from intentions and intentions are formed by specific attitudes toward the behaviors in question and subjective norms
WA	Walking	

Chapter 1: Introduction

1.1. Motivation

After a long history of development, the automobile industry has been now making it much easier for people, particularly in developed countries, to buy a car. Shifting to a car means that a number of barriers for public transport travelers, such as bus timetable not matching or unavailability of bus in short trips, will be eliminated which leads to more freedom in traveling. The increases in travel demands quickly become noticed by environmentalists and planners who are seeking for a sustainable balance between human activities and natural resources. As far as the concept 'resource-efficiency' is of concern, mobility with the associated issues of travel length and mode choice is crucial to energy sustainability (Camagni et al., 2002). Attracting more people to public transport, as a measure of promoting modal shifts, is one strategy toward sustainable mobility paradigm (Banister, 2008). Reducing car use in this way is sometimes called a "pull measure" (Steg, 2003b).

Efforts toward promoting travel behavior changes should ideally start with a firm theoretical basis. In social science, interventions are made with the knowledge of causality (Marini and Singer, 1988). If a causal relationship between an independent variable X and a dependent variable Y is assumed, then causing a change in X (e.g., making interventions) can produce a subsequent change in Y (e.g., getting the desired effects). Thus, a causal model is crucial for any intervention scheme. In practice, the frameworks used for modeling causality are fairly different among economists and psychologists. The main distinction lies in the notion of rationality (Ben-Akiva et al., 1999). Whereas economists base strongly on the rational aspect of the behavioral decisions, psychologists on the other hand view behaviors as both irrational and rational (Simon, 1986). The underlying assumption in econometric models is that "*the rational man of economics is a maximizer, who will settle for nothing less than the best*" (Simon, 1978), and that "*Rational behavior is behavior that maximizes utility*" (Rachlin, 1980). Thus, the cause of a behavior in the view of economists is the expected utility derived from performing that behavior. The term "utility" can be understood as any positive connotations (Rachlin, 1980), such as the feeling of comfortable or safe while traveling, instead of being restricted to tangible attributes such as time and cost. An individual may choose to drive for his commute because of the valuable travel time saved from fast traveling, and the main concern of a bus user can be traffic safety which motivates him to use bus. On the other hand, psychologists explain behaviors by more abstract factors, such as attitudes, normative values, or altruism. For instance, the Theory of Reasoned Action (TRA) (Ajzen and

Fishbein, 1980; Fishbein and Ajzen, 1975) and its extended version, the Theory of Planned Behavior (TPB) (Ajzen, 1991) formulate the behaviors as being caused directly by (behavioral) intentions. Intentions are then assumed to be caused directly by attitudes, subjective norms, and perceived behavioral controls. Applying this notion to transportation, a decision to use bus can be caused by a bus use intention, and this intention is then formed by the positive attitude toward bus use, some social pressures to use the bus, and perceived controls for bus use. Clearly, human behaviors are not always rational in specific contexts and, thus, irrational behaviors might be poorly explained by econometric models. This does not necessarily imply that psychological models can always explain irrational behaviors better, nevertheless the basic assumption of rationality of econometric model is challenged in these cases. This fact was confirmed by experiments in both psychology and economics literature (DellaVigna, 2009). It was not unsurprising that psychological economists have proposed econometric models that incorporate as many as psychological factors for better behavioral explanations. In recent travel mode choice studies, psychological factors such as attitudes, lifestyle, and habits were found to be better determinants of mode choice behaviors than conventional objective variables (De Vos et al., 2016). In choice behavior analysis for example, the Integrated Choice and Latent Variable (ICLV) models are increasingly employed in various choice behavior domains. However, even psychological aspects have been embedded into econometric models, it is worth noting that utility maximization is still the fundamental component in the conceptualizations of these models. In a similar vein, taboo trade-off aversion was proposed as a remedy for the morally problematic assumption of directly trading off between observable variables and latent variables in conventional ICLV models (Chorus et al., 2018).

The above discussions suggest that psychological factors should not be ignored in designing behavior change interventions if one is seeking for determinants of both rational and irrational behaviors. Motivated by this idea, this dissertation is an effort in examining the effects of two attitudes, including environmentalism[1] and Attitude toward Physical Activity (APA), on several forms of travel behavior. The focus on these attitudes was due to three main considerations.

First, from policy perspective, general attitudes such as environmentalism and APA exhibit wider influential ranges on behaviors (Rokeach, 1980) and more exogeneities to behaviors

[1] Environmentalism can be considered attitudes toward human's impacts on global environment (Fransson and Gärling, 1999).

(Kroesen and Chorus, 2018) than specific attitudes[2] and, hence, appearing to be more fruitful for travel behavior interventions (e.g., multiple behavioral changes as a result of a sole intervention). Not being restricted to specific travel behaviors, such forms of general attitudes can cover any issues deemed to be significant to the policymakers. In some sense, the focus on general attitudes offers more flexibilities for the policymakers in designing travel behavior interventions based on attitudinal measures.

Second, both attitudes are related to the current issues of modern life. Inactivity caused by work environments and car dependency (Bull et al., 2010) linked to a number of health problems, such as coronary heart disease, type 2 diabetes, breast and colon cancers, and shortens life expectancy (Lee et al., 2012). The benefits of maintaining regular physical activities to health have been well acknowledged (Harris et al., 1989), and raising physical activity levels has been recognized as a primary object of health sector (Heath et al., 2012). At society level, Dunlap (2000) noted that environmental problems in recent decades have evolved significantly from common issues, such as pollution or hazardous waste, to more complex and dispersed issues with less directly observable and more ambiguous origin[3]. The relevance of environmentalism and APA to the issues that people worldwide and every country have to face with illustrates their significances to social policies.

Third, exploring multifaceted factors potentially benefits public policies. The process where a public policy is made has transformed from approaches of identifying the knowledge-based "best solution" to methods guided by the analysis of pros and cons and outcome patterns (Hassel, 2015). Yet, cost-benefit analysis remains the most common tool for both researchers and practitioners in evaluating public policies (Ferretti et al., 2019). In this aspect, the potential marginal effects on transport domain of environmentalism, one of the important issues for socialists and pro-environmentalists, and APA, a factor rooted in health science, would be worth pursuing. Such cross-discipline effects, if proven, would provide supportive or discouraging arguments for the cost-benefit analyses of the corresponding policies.

In short, we expect that examining the effects of environmentalism and APA on travel behaviors can lead to various benefits for both the literature and practice. The remainder of this chapter is organized as follows: Section 1.2 gives the research objectives; Section 1.3

[2] In general, attitudes can be defined as an individual's tendency to evaluate an entity with a certain level of favor/disfavor (Eagly and Chaiken, 1993). Depending on the types of entities, attitudes can be specific (i.e. when the entities are specific behaviors, such as traveling by bus or car) or general (i.e. when the entities are general objects, such as environmental protection and physical activity).

[3] For illustration, pollution may extend to global scale, contain many complex causes, such as interactions between different industries, and being not straightforward to figure out the scale of the problem.

gives an overview of the state of the practice in the effects of general attitudes on travel behaviors; Section 1.4 summarizes the contributions of this dissertation and; Section 1.5 describes the dissertation's structure.

1.2. Objectives

By examining the effects of environmentalism and APA on several travel behavior forms, including travel mode choice behaviors, car use behaviors, and Bus Use Intentions (BUI), this dissertation has three distinct objectives.

First, findings of this dissertation are expected to support designing social policies of multiple sectors, including transport, health, and environment. We believe that the continuously changing world always brings new issues to human life that social policies must take into consideration. Traveling, physical activities, and environmental cares are important social issues for any country. Any evidence suggesting/disproving causal relationships between environmentalism, APA, and travel behaviors can be a reference source for policy considerations that will have great impacts on the whole society. An idea that this study pursues is to suggest combined policies, e.g. transport and health policies, as a more cost-effective solution. Such intuitive combinations, however, still need to base on empirical evidence, and the findings from this study were expected to serve for this purpose. In addition, environmentalism and APA represent for two types of benefits, that are contradictory in some sense. Environmentalism shows how an individual cares for the global environment, which can be considered as a form of cares for social benefits. In contrast, APA reflects how one cares for his/her physical health, which is an indication of the cares for private benefits. By comparing the effects of these two factors on travel behaviors, we can see how interests in private benefits and cares for social outcomes would take part in travel decisions. This would be useful in evaluating the feasibilities of social intervention campaigns when a number of behavior domains are on the table.

The second objective of this dissertation is to contribute to the literature in travel behavior analysis by expanding the range of determinants of travel behaviors and travel intentions. To date, the number of general attitudes investigated in travel analyses is fairly limited. This dissertation attempts to expand the range of determinants of travel behaviors by considering new forms of general attitudes.

Finally, the dissertation aims at contributions to the methodologies in examining the effects of psychological factors on (travel) behaviors. By employing different methodological frameworks in examining the particular relationships between environmentalism and APA and travel behaviors, we first propose a general approach in studying the effects of psychological factors on behaviors. Then in conducting individual case studies, the practices in solving individual problems characterized by their own study contexts will uncover new methodological improvements.

To realize these objectives, the study first developed frameworks for the target effects. Then we collected data for estimating the proposed models. Finally, we interpreted the model estimates and suggested practices for transport policies.

1.3. The effects of general attitudes on travel behaviors: A brief overview of State-of-the-Practice

To date, a number of attitudes have appeared in the literature of travel behavior analyses. The investigated attitudes ranged from attitudes toward a specific characteristic of travel behaviors, such as flexibility, convenience/comfort and security (Daziano and Rizzi, 2015; Morikawa et al., 2002; Paulssen et al., 2014; Temme et al., 2007; Vredin Johansson et al., 2006), attitudes toward a specific transport mode (Donald et al., 2014; Lois et al., 2015; Noblet et al., 2014; Nordfjærn et al., 2014; Ru et al., 2018), to attitudes toward a general entity, such as environmental concerns (Atasoy et al., 2013; Donald et al., 2014; Roberts et al., 2018), political attitudes (Kroesen and Chorus, 2018) and physical activity (Kamargianni et al., 2015).

Environmentalism appeared inconsistently in its conceptualization in previous studies, such as under the name of pro-environmental preference (Vredin Johansson et al., 2006), attitude toward the environment (Sottile et al., 2015a), or environmental attitudes and behaviors (Roberts et al., 2018), and more importantly, the ecological aspects of recent global problems were not dealt with. In the literature, studies showed inconsistent results regarding the effects of environmentalism on travel behaviors although the main finding is its positive effects on the choices for mass transport (Bouscasse, 2018). Supports for this intuition were shown in cases where high environmental concerns reduced car choices, such as in Roberts et al., (2018), where environmental concerns reduced car use habits (Bouscasse et al., 2018; Donald et al., 2014), where environmental preference was found to increase the likelihood of choosing train versus a less environmentally friendly mode, bus (Vredin Johansson et al., 2006), and where people with positive attitude toward environment protection were more likely to choose public transport (Atasoy et al., 2013; Kim et al., 2012; Schüssler and Axhausen, 2011). However, there are also cases where the effects of environmentalism were found to contradict the expectations, such as environmental attitude was found to increase car utility in a mode choice situation between car and park-and-ride options (Sottile et al., 2015b), or environmental beliefs were found to promote car uses in choice situations between bus/taxi/carpool versus car (Politis et al., 2012). Similarly, the intuitive causal relationship between environmental concerns and car use has been challenged in a number of studies. Meta-analysis studies found weak, but expected, negative correlations between environmental concerns and car use (Gardner and Abraham, 2008; Lanzini and Khan, 2017). Even when people were aware of the environmental problems, mass media campaigns still failed to reduce car use (Tertoolen et al., 1998). Particularly, two cases were found in which environmental concerns increased car use (Politis et al., 2012; Sottile et al., 2015b). Tertoolen et al. (1998) explained this inconsistency between environmental concerns and car use by social dilemmas and cognitive dissonance. People tend to care more about immediate advantages of car use, such as freedom and independence, than long-term consequences for the society and for themselves due to their collective car use, and hence, awareness of consequences to the environment can fail to reduce car use. Similarly, the awareness of environmental consequences due to car use can cause psychological distress to frequent car users. To mitigate this distress, people can change their behaviors, such as to reduce car use, or change their attitude, such as to think about car use as being less harmful to the environment than it really is; the latter case was observed by Sottile et al. (2015) and Tertoolen et al. (1998).

In contrast, very limited studies considered the factor APA in travel behavior analysis. The study of the influence of physical activity propensity on mode choice (Kamargianni et al., 2015) is the only one we found, but this study is limited to the mode choice of teenagers.

1.4. Contributions

The most important contribution of this thesis is our overall suggestion that there is a possibility of intervening people's environmentalism and APA so that transport, health, and environmental goals can be achieved. In Chapter 4, we found an association between environmentalism and the choice of rail, but an expected effect of environmentalism on car use was not found in Chapter 6. Similarly, we found positive effects of APA on the mode shares and utilities of bicycle and walking. APA was also found to have an effect on bus use intention and bus choice. Thus, we suggest that to promote PT, such as bus and rail transport, and active transport, such as cycling and walking, raising people's environmentalism and APA can be a solution. For car use reduction, we suggest that policymakers may consider factors other than common socio-demographic characteristics and environmentalism (e.g., factors of highly abstract level such as personal values). This facilitates a proposal of combining transport policies with health and environmental policies as a cost-effective solution for social policy designs. The comparison between the effects of environmentalism and APA on traveler mode choice revealed that the interests in personal benefits, such as physical health benefit, are stronger than cares for social benefits, such as the protection for the ecology system. This implies that the effectiveness of intervention campaigns might be higher if personal benefits are more targeted, and is in line with the idea of social dilemmas that people tend to care more about immediate private benefits than long-term consequences for the society.

For the literature in travel behavior analysis, we suggest that environmentalism and APA should be considered determinants of travel behaviors and intentions. Specifically, environmentalism should be a determinant of rail use and not of car use, and APA should be a determinant of bus use intention and active transport (e.g., cycling and walking). This result may serve as a call for future studies in including environmentalism and APA in the frameworks of travel behavior analyses. Environmentalism and APA can also be linked to factors of higher abstract levels or more complex behavioral theories in explaining travel behaviors.

Some methodological suggestions for the literature can be summarized as follows. For choice modeling, we have emphasized the importance of heterogeneity treatments, particularly when the analyst wants to uncover the loose relationships between psychological factors and mode choice behaviors. The result in case study in Chapter 4 revealed that the effect of environmentalism on mode choice was hidden when being examined using pooled data, and it was uncovered in the framework of latent class choice model where heterogeneity was treated. This result also suggested that the effects of latent variables can be examined though analyzing mode share patterns instead of the conventional way of analyzing them through utility functions. In that case, we suggested the analyst to use supportive analyses to confirm the result (e.g., sensitivity analysis and validation analysis). In addition, by introducing the bias correction method for binary choice models in Chapter 5, we proposed a solution for choice modeling in case of highly unbalanced mode shares. This might be particularly useful for transport studies in rural areas in developed countries as car use generally dominates other mode uses in these areas. For travel behavior analysis, we confirmed the usefulness of employing mediators in relating general attitudes to behavioral intentions as they helped to increase the regression coefficients of the relationships. The mediators also improved the percentage of variance explained of the model for the target variable (e.g., bus use intention). We also suggested the use of single-indicator latent variables in SEMs. Additionally, we showed how enabling reciprocal relationships in relating latent variables helps to identify the best models in terms of fitting the observed data.

1.5. Outline of the dissertation

The dissertation was structured as follows. In **Chapter 2: Psychological background**, we presented theoretical basis derived from psychology, from that the methodological frameworks are based. As environmentalism and APA are the focus of this dissertation, the chapter started with a review on attitude concept. Then, how attitudes can be linked to behaviors, including travel behaviors, through several behavioral theories and cognitive processes was presented. Two particular issues, the relationship between general attitudes and specific attitudes, and the measurements of environmentalism, were given more discussions. Then **Chapter 3: Methodological frameworks** went into detail the two main frameworks employed in this dissertation, a choice model framework and a Structural Equation Model (SEM) framework. *In the choice model framework*, we first introduced the logit model, including its specifications, underlying assumptions, and estimations issues. Then, we introduced the error component logit mixture model that allows modeling correlations in repeated choices. Two advanced forms of the logit model followed. In the ICLV model, latent variables such as environmentalism and APA can interact directly and linearly with other mode utility's components. The Latent Class Choice (LCC) model was introduced as a heterogeneity treatment solution in choice modeling. The chapter ended with a special issue of how to remove bias in parameter estimates of binary choice models due to highly unbalanced mode shares. *In SEM framework*, we started with the introduction to Principal Component Analysis (PCA) which helped to identify factors from a given set of indicators. Then, the frameworks of SEMs were given. To fully explore the potential effects of environmentalism and APA on various travel behaviors, Chapter 4, 5, 6, and 7 presented the applications of the frameworks in Chapter 3 to four case studies. In **Chapter 4: ICLV and LCC framework for examining the effects of environmentalism and APA on mode choice behaviors,** the effects of environmentalism and APA on travel mode choice behaviors were examined simultaneously using a multinomial mode choice model. Data from 1840 trips made by 821 respondents living in Nagoya, Japan, were used for estimating an ICLV model and a LCC model of a choice set including car, rail, cycling, and walking. The estimation result confirmed the effect of environmentalism on the choice of rail. APA was found to cause both the utilities and choices of cycling and walking. **Chapter 5: Examining the effect of APA on mode choice behaviors with parameter bias correction** re-examined the effect of APA on mode choice, but with a bias correction method employed and in a binary choice context. In this case, APA was modeled to have indirect effects on mode choices between car and bus, specifically through its effect on specific attitudes toward bus use. The parameter estimates were corrected using Firth method as data separation being found in the input data. Two binary ICLV models were sequentially estimated using data of 591 clinic/hospital trips and 734 shopping trips of respondents living in Asuke, Japan. The estimation result showed that APA had a significant indirect effect on bus utility and the bias correction method helped to reduce standard errors. In **Chapter 6: The reciprocal relationships between environmentalism and car use behaviors**, we examined the potential effect of environmentalism on car use behaviors. This examination was expected to contribute to transport policies in car use reduction. A number of specifications for SEM were tested, including complex relationships such as reciprocation and correlated residual terms. Data from 900 respondents living in Nagoya were used for model estimations. However, we did not find significant effect of environmentalism on car use. Instead, we found a significant negative correlation between these factors, implying that identifying the hidden causes for both factors can benefit both environment and transport policies. **Chapter 7: The effect of APA on bus use intentions** differed slightly with previous chapters where we shifted our focus from travel behaviors to one of their immediate determinants, the travel intentions. Specifically, we employed SEM to examine the effect of APA on BUI. Data from 1604 respondents living in Asuke were used for estimating a base model, where APA directly caused BUI, and an extended TPB model, where three TPB's variables mediated that relationship. We found significant effect of APA on BUI in both models. However, the effect was found stronger in case of using mediators. In addition, the multiple-group analysis revealed that the effect differed between several cohorts. Finally, **Chapter 8: Conclusions and future directions** gave our general conclusions and potential directions for future studies.

Chapter 2: Psychological background

As this dissertation is featured by a strong psychology background in analyzing travel behaviors, this chapter attempted to collect necessary material and knowledge from psychology to support developing the frameworks be used in later case studies. As such, the outcomes of this chapter were a direct input for Chapter 3. We started by briefing understandings on attitudes and the current literature related to attitudes, which is the main object of this dissertation. Then, as most studies in psychology and sociology focused, we examined the theoretical bases for the effects of attitudes on behaviors. We introduced two well-known and frequently cited behavioral theories that were later applied directly or indirectly in case studies in Chapter 5, 6, and 7, the MODE model and the TRA/TPB model. Two specific issues related to attitudes were given more discussions, the relationships between general attitudes and specific attitudes, which their discussions were applied directly to case studies in Chapter 5 and Chapter 7, and conceptualizations for environmentalism, which were necessary for the measurement models in case studies in Chapter 4 and Chapter 6.

2.1. An overview of the construct attitude

The attractiveness of attitudes in sociology and psychology was pointed out by the famous dictum by Allport (1935) that attitudes are "the most distinctive and indispensable concept in American social psychology." In fact, psychology was originally defined as the scientific study of attitudes because understanding of this construct is considered the key to explanations of human behavior (Fishbein and Ajzen, 2009). Unsurprisingly, a clear and comprehensive definition of attitude was the goal of a number of studies in the literature (Albarracín et al., 2005). In this dissertation, we restrict these definitions to the one suggested by Eagly and Chaiken (1993) that an attitude is an individual's tendency to evaluate an entity with a certain level of favor. The followings present basic understandings related to the concept attitude.

The structure of attitudes

A number of studies in psychology considered attitude structure to have three elements, including affect[4] (e.g., the positive/negative feelings/moods about attitude objects), cognition (e.g., the beliefs hold toward attitude objects), and behavior (e.g., the overt actions toward the attitude objects) (Fabrigar et al., 2005). It was also acknowledged that attitudes have reciprocal impacts on affects, beliefs, and behaviors, and these phenomena, on the other hands,

[4] As certain ambiguities remains in distinguishing between attitude and affect, Fishbein and Ajzen (2009) suggested to view attitude as evaluations and affect as mood and emotion states.

constitute or transform attitudes (Albarracín et al., 2005). Kruglanski and Stroebe (2005) even considered attitudes, affects, goals and behavioral information being different sorts of belief. These evidence partly reflect the complexity in attitude structure.

Attitudes were traditionally considered affective processes (Walther and Langer, 2008), such as positive and negative feelings/moods toward the attitude objects. A common concept that leaded to this notion was Evaluation Conditioning (EC), referring to the changes in the degree of liking/disliking a stimulus as a result of pairing it with other positive/negative stimuli many times. Following this notion, attitude is thus considered being formed by mere associations of affective cues (Walther and Langer, 2008). The robustness and ubiquity of EC were evidenced in a number of stimuli and procedures (De Houwer et al., 2001).

Recently, a number of studies in psychology viewed attitudes as cognitive processes where certain cognitive efforts, commonly evaluations, contribute to the formations of attitudes (Albarracín et al., 2005; Fishbein and Ajzen, 2009). For example, Eagly and Chaiken (1993) considered attitude as the evaluations of attitude objects with a certain level of favor/disfavor, Fazio et al. (1986) considered attitudes as associations between an object and an evaluation of that object with varying strengths, and Ajzen (1991) formulated (specific) attitudes as an evaluation system for the positive/negative outcomes of performing the behaviors in question. Unlike the conceptualization of attitudes as affects, this attitude notion explicitly admits a deliberate thinking process in the formations of attitudes. A well-known theory of this branch was the expectancy-value model (Fishbein, 1963). The model formulated attitudes as being the summations of subjective *values* of attributes of an object multiplied by the *expectancy* of these values.

Walther and Langer (2008) considered both affects and cognitions as different phases of attitude formation and change, such as affects first form the attitudes and cognitions after that change the attitudes. In addition to the personal factors, social influence is also an important determinant of attitude as people form their attitudes in reciprocal relations with others in the society (Prislin and Wood, 2005).

The stability and variability of attitude

In considering attitudes as being formed by evaluating different aspects of attitude objects, typically in Fazio et al. (1986) and Ajzen (1991), these conceptualizations explicitly treated attitudes as stable cognitive structures residing in memory and being available immediately at the moment of facing an attitude object. However, there are reasons for the fact that attitudes need not necessarily to be stable over time. A number of contextual factors may be involved into the formation of attitude at a particular point. For example, people's judgments are often based on the external information that is temporarily available at the context, in addition to previously knowledge stored in memory (Albarracín et al., 2005). This is particularly true for the common way of measuring attitude based on self-reporting. A number of contextual factors may contribute to how the respondents interpret/answer the attitudinal questions, such as question comprehension, recalling relevant information, inference rules, and so on (Schwarz and Bohner, 2001). It was thus suggested that evaluation judgments in measuring attitude are 'constructed on the spot', i.e., highly contextually dependent.

Attitude accessibility

A key concept in studying attitudes is attitude accessibility, being understood as the frequency of attitude activations (Fabrigar et al., 2005; Fazio et al., 1986). Attitude accessibility, or attitude strength, refers to how many times attitudes were strengthened in the past through repeated activations. Thus, stronger attitudes are expected to affect future behaviors more than weaker attitudes, other things being equal. Different attitude's elements may have different accessibilities. For example, affect was observed to be more accessible than cognition in extreme attitudes, but being less accessible with less extreme attitudes (Giner-Sorolla, 2001).

Attitude measurement

The conventional way of measuring attitudes is by asking the respondents to give their evaluations on attitude objects (e.g., on a Likert scale). Underlying these measurements is an assumption that people's attitudes are unique and stable. However, researches on attitudinal ambivalence showed that people may hold both a positive and a negative attitude toward the same object (Kruglanski and Stroebe, 2005), which can be seen as an obstacle for both attitude measurements and conceptualizations. Depending on how the analyst defines attitudes, attitude measurements can cover a wide range of mental and neural human states, such as in Allport (1935), to focus on a particular entity, such as in Eagly and Chaiken (1993). Krosnick et al. (2005) described a general three-stages cognitive procedure that the respondents may follow in responding to attitudinal questions, given in Figure 1.

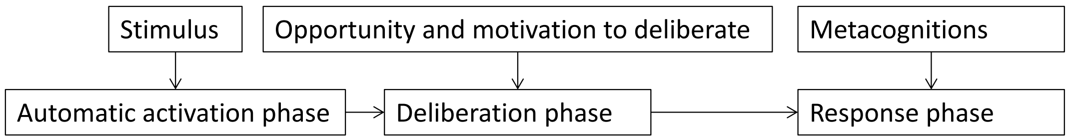

Figure 1. Three stages in reporting self-evaluations of attitudinal objects, adapted from Krosnick et al., (2005).

These explicit measurements of attitudes are, however, prone to containing certain over/underestimations (Krosnick et al., 2005; Van Exel and Rietveld, 2009). Social biases in self-reported evaluations are understandable, as flattering self-portraits are generally desired. Similarly, these direct methods are based on the conventional assumption that attitudes operate in a conscious mode, e.g. the respondents rely, recall, or trace past experience related to attitude objects in order to form their attitudes toward these objects. However, evidence showed that some influential experiences affect behaviors in an unconscious manner (Greenwald and Banaji, 1995), that is, the actors are unaware of the existence of these experience but they still affect the actor's behaviors. Greenwald and Banaji then proposed an indirect measure for assessing attitudes that is basically based on unconscious cognition and, thus, potentially excluding out social biases. This appeal has led to various implicit measurement techniques in the literature, for example the Implicit Association Test (IAT) by Greenwald et al. (1998), or employing non-verbal behaviors, although many firm conclusions could not be reached (Fazio and Olson, 2003; Fishbein and Ajzen, 2009). In addition, psychologists generally agreed that implicit measures of attitude might better predict unconsciously monitored behaviors but not volitional behaviors because social desirability may also have an effect on actual behaviors (e.g., people tend to not engage in socially undesirable behaviors) in addition to its effect in biasing the self-reported responses on a questionnaire (Fishbein and Ajzen, 2009). Social desirability concerns was found being an important factor in the relationship between implicit attitude and explicit attitude (Bassili and Brown, 2005).

Given any measurement method of attitude, the researcher may still face some inherent problems, such as the nature of being latent of attitude, non-existence of single attitude stored in memory, or having multiple attitudes toward the same object (Fabrigar et al., 2005; Krosnick et al., 2005).

Attitude interventions

The traditional way of changing one's attitude is through verbal messages with advocated views introduced to the recipients. Typically, attitude change is expected as a result of a direct link between the evaluative information and the attitude object (Walther and Langer, 2008). In such cases, the effectiveness of persuasions depends on the used inference rules and metacognitions of the recipients (Kruglanski and Stroebe, 2005).

Attitude can also be changed due to cognitive dissonance phenomenon. The inconsistencies between one's own behaviors, i.e. car use, and socially desirable behaviors, i.e. mass transport use to protect the environment, can create an unpleasant state, or the cognitive dissonance, that he/she may want to reduce. These can be done by changing behaviors, i.e. to shift to mass transport, or by changing attitude, i.e. to think that car use is not environmentally harmful. In the latter case, the individual's attitude toward car use will become more positive.

Recent interests in attitude change studies have been given to Elaboration Likelihood Model (ELM) (Petty and Cacioppo, 1986) and Heuristic and Systematic Model (HSM) (Chaiken, 1989), two persuasion mechanisms. ELM postulated that people can have varying levels of elaboration in an attitudinal persuasion context. Toward the higher end of this continuum, i.e. much elaboration about the persuasion information, the received information will be processed via the central route which will result in attitude changes that last long over time. In contrast, little thoughts will tend to make attitude to change in the peripheral route where the resultant attitude changes are expected to be less durable. HSM, on the other hands, assumed that people process the persuasion information either systematically, including carefully processing the message or information scrutiny, or heuristically, as a way of minimizing cognitive efforts, or both.

Evidence in the literature generally suggested that the more accessible attitude is, the harder it can be changed (Fabrigar et al., 2005). Similarly, ambivalent attitudes were found being susceptible to persuasions (Armitage and Conner, 2000).

2.2. The effects of attitudes on behaviors

Of a particular interest in this chapter is the effects of attitude on behaviors. Although an opposite idea, such as the effects of behaviors on attitudes, was recognized in the literature (e.g., see Olson and Stone (2005) for a review), we restrict these relationships to unidirectional effects of attitudes on behaviors. Insights into this topic will provide a theoretical basis for the frameworks of examining the effects of environmentalism and APA on travel behaviors.

Early studies on behavioral predictabilities of attitudes showed disappointing results when the attitude-behavior correlations were found fairly weak (Ajzen, 1991; Fishbein and Ajzen, 2009; Kraus, 1995; Walter Mischel, 1968; Wicker, 1969). Zanna and Fazio (1982) posed the question "is there a relation between attitudes and behavior?", and Wicker (1969) even called for the abandonment of the attitude concept due to this failure. Possible explanations were suggested, such as the failure of the investigators in excluding social desirability and, hence, reducing response biases, or the multiple-dimension nature of attitude (Ajzen and Fishbein, 2005). However, later studies revealed that these effects become clearer and strengthened with the presence of moderators, such as specific attitude toward the behavior and perceived normative expectation (Ajzen and Fishbein, 1973), self-monitoring (Snyder and Kendzierski, 1982), and level of moral reasoning (Rholes and Bailey, 1983). Similarly, Bamberg (2003) strongly criticized the incorrect assumption about a direct effect from an attitude, such as environmental concern, to environmentally related behaviors. He also signified that this attitude is an important indirect determinant of specific behaviors. The improvements in attitude-behavior consistency brought by the mediators are, explained by Ajzen and Fishbein (2005), due to the fact that attitudes reflect (general) evaluations of an object whereas a behavior related to that object must be referred to a given (specific) context. Ajzen and Fishbein (2005) further suggested that a general attitude can still be consistent with multiple behaviors that are representative of the same behavioral domain. For the specific behaviors, the levels of consistency depend on the level of specificity of the behaviors in question.

In psychology, several behavioral theories have examined the mechanisms, or the processes, where attitudes affect behaviors. In the followings, we introduce two well-known theories that served as the theoretical basis of our examination on the effects of environmentalism and APA on travel behaviors.

2.2.1. The MODE model

The MODE model (Fazio, 1990; Fazio et al., 1986; Fazio and Towles-Schwen, 1999), with the acronym MODE referring to the 'Motivation and Opportunity to serve as the major Determinants' of two attitude-to-behavior processes, spontaneous versus deliberative, is the most 'direct and sophisticated' model of attitude-to-behavior in the literature (Ajzen and Fishbein, 2005). Fazio (1990) initiated the development of the MODE model by confining the human cognitive processes leading to behaviors to two distinguishable processes: A deliberate cognitive process where trading-offs between benefits and costs as a result of performing the behaviors are made and; A spontaneous cognitive process where trading-offs do not happen. This distinction is similar to other ways of classifying decision making processes, such as rational versus irrational or compensation versus non-compensation. A crucial aspect of the

MODE model was the logic of accessibility. Accordingly, the strength of attitude is defined by the association between the attitude object and the subjective evaluations of that subject. The stronger this association is, the more accessible the attitude is. Attitudes with more accessibilities are therefore more likely to be activated. This logic is given in Figure 2.

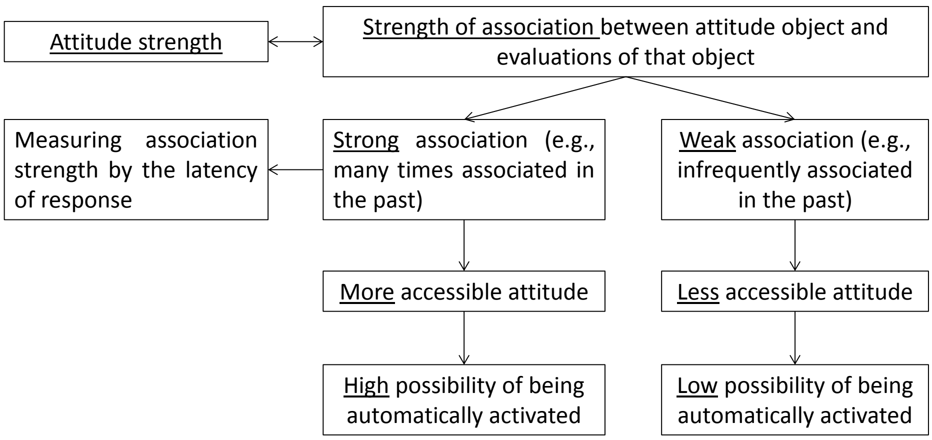

Figure 2. The concept of attitude accessibility in the MODE model.

The spontaneous processing model was proposed to be relevant with spontaneous behaviors, which are believed to be the most common type of human behaviors. When encountering the attitude objects, people are assumed to base on the perceptions and interpretations of these objects in coming to the behavior. For quick and immediate interpretations required in spontaneous decision makings, people may rely on the priming of previously formed constructs rather than utilizing cognitive skills (e.g., trading-offs). This is where attitude, as being one among other constructs, plays its role through *influencing the interpretations of the objects*. In Figure 3, this influence of attitude on behavior is illustrated in Process 1. In this process, attitudes serve as a knowledge resource immediately available for quick behavioral decisions. Further, whether attitudes stored in memory are activated depends on their accessibility, or the strengths of the associations between attitude objects and evaluations of these objects. Thus, attitudes may still fail to influence behaviors if the associations are not strong enough. This protocol of automatic activation of strong attitudes was challenged in several empirical studies. For example, Bargh et al. (1996) found evidence that attitudes were automatically activated when individuals were presented with attitude objects regardless of their strengths.

For deliberate and planned behaviors, a deliberate processing is more likely to occur. The interpretations of the attitude objects in this case are considered to be based on cognitive works, such as considering/weighing the attributes, costs, or benefits related to the behaviors.

The fear of invalidity due to the importance of the behavioral decision (e.g., the behavior is consequential) can force people to engage in a deliberate cognitive process (Kruglanski and Freund, 1983). This *motivation*, combined with the existence of *opportunity* to deliberately think (e.g., no time limitation for decision making), can finally result in a deliberate cognitive process. The MODE model then based on TRA and TPB, which are described in detail in the next sub-section, in arguing that: (1) These cognitive works will result in the formation of new *specific attitude toward the behavior*, which guides the behavior through its effect on the intention and; (2) If there is a strong similarity between the current behavior context and the context in the past where an attitude toward the same behavior was formed, the formation of this new attitude toward the current behavior may not be necessary. In case a new (specific) attitude is formed toward the behavior, activated and stable-over-time attitude toward the object may bias the perceptions of the behavior by enhancing the likelihoods of being considered of beliefs that are congruent with the attitude toward the object. In Figure 3, this influence of attitude on behavior is illustrated in Process 2. In other words, the model assumed a *selective retrieval mechanism* for beliefs to be included in the perceptions of behaviors.

The identification of two cognitive processes in the MODE model do not imply that they operate independently in the same decision making process. Instead, the model's author suggested the co-existence of multiple cognitive processes within the same behavior. Although the MODE model could not help to quantitatively judging which kind of behavior is more susceptible to attitude, it at least demonstrated the possible ways that attitude can guide behaviors.

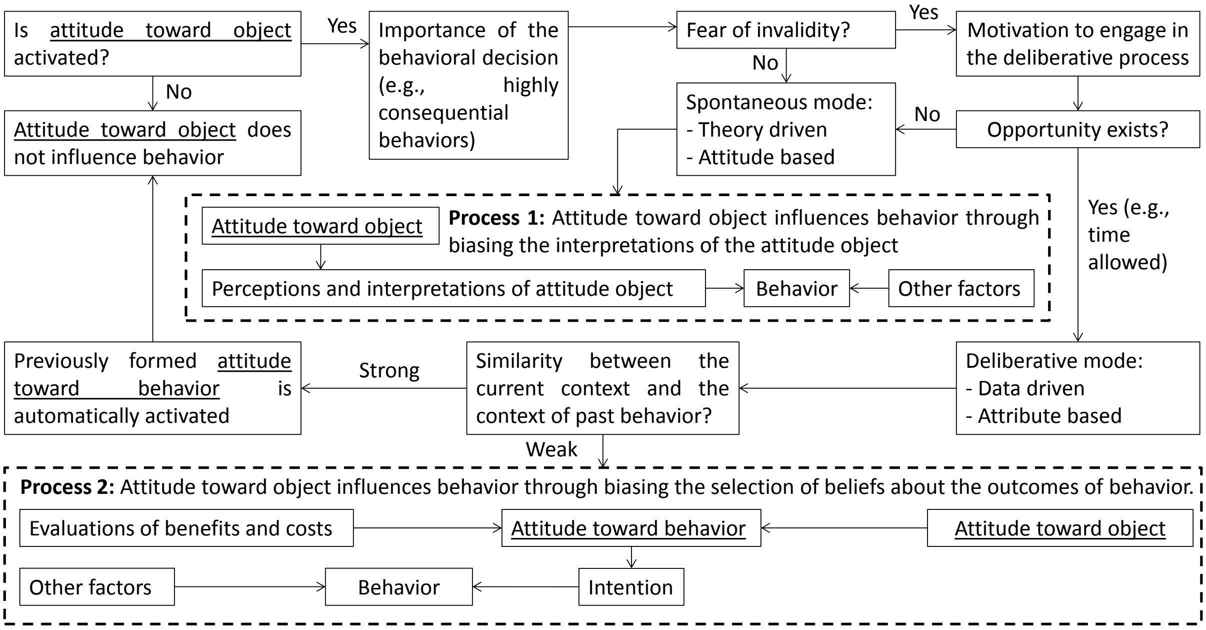

Figure 3. The two cognitive processes where attitude influences behavior postulated by the MODE model and the TPB model.

Note: Two dashed rectangles represent the two processes where attitude can influence behavior. The notion of TRA/TPBT is applicable in Process 2. The one-way arrows within the dashed rectangles denote unidirectional causal effects, whereas those outside the dashed rectangles show the possible directions of inference flows.

2.2.2. The theory of reasoned action and the theory of planned behavior

In the literature, TRA and TPB were extensively employed to model various behaviors. These theories assume that behaviors are guided by intentions and perceived behavioral controls, a factor that accounts for the gaps between intentions and actual behaviors. In turn, intentions are directly caused by *specific attitudes* toward the behaviors, and other factors including subjective norms and perceived behavioral controls. Both theories are based on the assumption of a 'reasoned' individual who will perform a specific behavior if he/she has the intention to do it, and the intention to perform a behavior is the outcome of the following three distinguished beliefs: (1) The belief that performing the behavior will result in more positive outcomes than negative outcomes; (2) The belief that important referent individuals will approve that behavior and; (3) The belief that he/she has sufficient requisite resources and opportunities to perform the behavior. The authors of TRA and TPB later added that their assumption of 'reasoned' action implies a reasonably and consistently transition from beliefs to intentions, whereas these beliefs can be reasonable or not (Fishbein and Ajzen, 2009). Figure 4 shows the theoretical models of TRA and TPB with factors (latent variables) related to each other through unidirectional effects. The predictabilities of predictors are generally assessed by considering their regression coefficients (e.g., the stronger the coefficients are, the bigger effects that these predictors have on the dependent variables). Empirical studies have provided rich supports for TRA, particularly in case of behavioral choice among explicit alternatives (Sheppard et al., 1988). For example, a meta-analysis of 185 studies found an average correlation coefficient of 0.47 between intentions and behaviors, and 0.49 between attitudes and intentions, and together TPB variables explained for 27% to 39% of the variances of intentions and behaviors (Armitage and Conner, 2001).

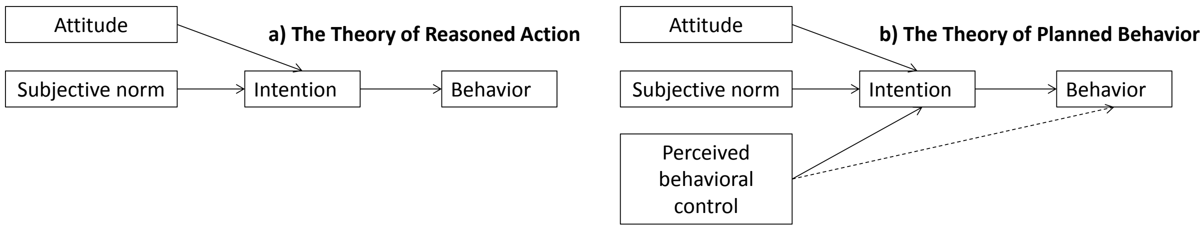

Figure 4. Structural diagrams for the theory of reasoned action (a) and the theory of planned behavior for explaining behavior (b). The dashed line implies that perceived behavioral control is a proxy of real factors that control behavior.

Clearly, the attitude measure considered in TRA and TPB is attitude toward a specific behavior, not a general attitude toward an object. However, Fishbein and Ajzen (2009) in following the principle of compatibility argued that specific attitudes are better predictors of behaviors than general attitudes. The specific attitude reflects the 'degree to which a person has a favorable or unfavorable evaluation or appraisal of the behavior in question' (Ajzen, 1991). This measure of attitude is treated as a total sum of multiplicative forms of the strengths of the salient beliefs, or the accessible beliefs (Fishbein and Ajzen, 2009), about the behavior and the subjective evaluations of the these beliefs. Accordingly, if the expected positive outcomes outweigh the expected negative ones, then attitude toward the behavior is considered being favorable and, subsequently, resulting in the intention to perform the behavior. This principle followed strictly to the expectancy-value model described in Section 2.1 and Section 2.3. The focus of TRA and TPB on specific attitude in an effort to raise the model predictability have, however, become one source of criticism on the value of using specific attitude (Fazio, 1990), which is less exogenous to the behavior than general attitude (Kroesen and Chorus, 2018).

2.3. The relationship between general attitudes and specific attitudes

This dissertation is concerned with environmentalism and APA, two general attitudes related to common objects of modern life. Their effects on human specific behaviors were, however, not straightforward to be discovered without investigating their relationships with factors closer to behaviors, such as specific attitudes toward behaviors. This topic has attracted a number of studies in the literature with the overall goal of understanding and/or explaining the generally weak correlations between general attitudes and specific behaviors. The findings from this topic can help answer questions such as can we expect a person with positive environmental and APA to also hold the same positive attitudes toward specific behaviors related to these objects, such as using PT and active transport. The discussions in this section were directly used as theoretical bases for case studies in Chapter 5 and Chapter 7.

Following the framework of the MODE model presented in Sub-section 2.2.1, a general attitude toward an object, i.e. physical activity, can remain its effect on a specific attitude toward a behavior related to that object, i.e. using a bus which contains more physical activity level than a car[5], if the general attitude has been strongly strengthened in the past. Presented in Figure 5 is an illustration for this notion of the MODE model. Fazio (1990) gave an example of the possible correlation between the overall attitude toward Reagan, one among the presidents of the United States, and specific attitude toward the behavior of voting for Reagan. Once the general attitude toward an object has been strengthened, the strong associations between that object and evaluations of its attributes can expand to any related specific behaviors. More specifically, strongly accessible attitude will ensure that only selected beliefs that are congruent with the attitude will be retained in forming the attitude toward the behavior. In the example in Figure 5, attitude toward physical activity can be theoretically considered to be the belief that "physical activities are beneficial for health." as generally attitudes can be treated as beliefs (Ajzen, 1991; Zanna and Rempel, 1988). When the attitude toward bus use is formed, this belief can shape the individual's selection of the beliefs related to bus use so that beliefs that are more congruent with positive attitude toward physical activity (e.g., the belief that bus use is beneficial for health due to having some physical activities) will have more chances of being considered. As a result, a person with accessible attitude toward physical activity will be more likely to hold the same positive attitude toward bus use.

[5] Evidence on the association between physical activity and public transport use can be found in research (Rissel et al., 2012).

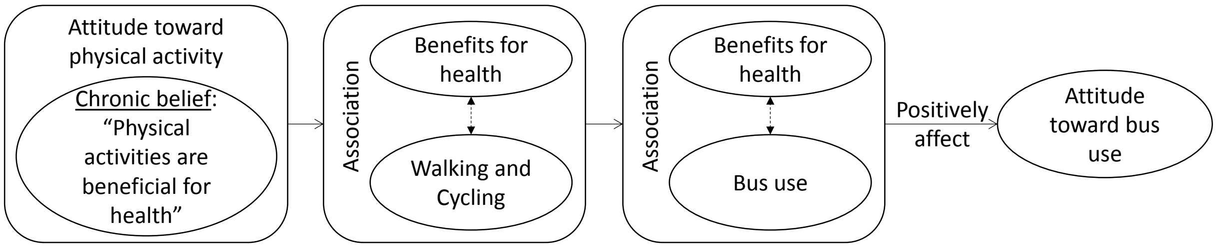

Figure 5. A structural diagram for illustrating the relationship between a general attitude, i.e. attitude toward physical activity, and a specific attitude, i.e. attitude toward bus use.

Note: the solid arrows represent the one-way effect, and the dashed arrows show the association between objects.

On the other hand, TRA and TPB, the two well-known theories that considered specific attitudes, offered another framework for understanding the relationship between general attitudes and specific attitudes. In TRA and TPB, the authors left open the question of how to acquire the specific attitudes (Fishbein and Ajzen, 2009). In fact, the TRA and TPB model can be viewed as a proximal model in a way that broad and personality traits, general attitudes, and other background factors can have indirect effects on the behavior through factors that are more closely linked to the behavior (Ajzen, 1991; Fishbein and Ajzen, 2009). This, thus, implies links from general attitudes and other background factors to TPB's variables including specific attitudes, as described in an enhanced model of TRA and TPB shown in Figure 6.

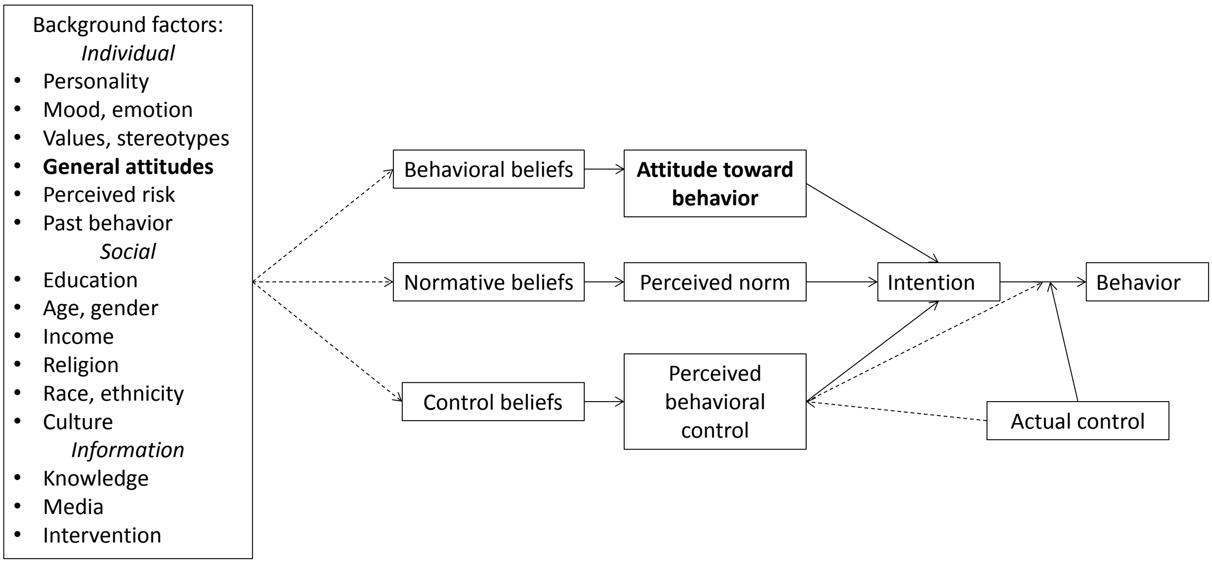

Figure 6. The reasoned action model, adapted from Fishbein and Ajzen (2009).

According to the reasoned action model, beliefs about the possible outcomes of the behavior in question are the direct determinants of the specific attitude toward that behavior. The model then based on the expectancy-value model (Fishbein, 1963) in quantitatively formulating the strengths of specific attitudes toward behaviors as a function of: (1) The strengths of salient beliefs about the outcomes of behaviors and; (2) The evaluations of these outcomes,

$$A \propto \sum b_i e_i \tag{1}$$

where A denotes the specific attitude toward the behavior, b_i and e_i are the strengths of salient beliefs and their evaluations, respectively. The beliefs about the possible outcomes of a behavior can be caused by directly experiencing these outcomes, by accepting information from outside sources related to that behavior, and by processing relevant inferences. Crucially, any background factors, such as personalities and general attitudes, which people who vary in terms of these factors will also vary in their beliefs of the behavioral outcomes, can be determinants of specific attitudes. For example, let us consider a person who values physical activities as being necessary for life and another person who pays no care in physical activities. Regarding to their beliefs on the outcomes of using bus, assumed to contain certain physical activities, we may expect that the former one will value bus use more beneficial than the latter one. This may result in the fact that the person with positive attitude toward physical activity will also have positive attitude toward bus use, and vice versus. This example and the theoretical basis underlying it thus make it possible to hypothesize an effect of a general attitude toward an object on the specific attitude toward a behavior related to that object. Further, the emphasis on the role of salient beliefs, instead of all beliefs, implies that beliefs that are readily available in memory will provide the main input for the (specific) attitude formation. Fishbein and Ajzen (2009) mentioned that the term salience should be replaced by the concept of accessibility, which emphasizes the role of belief accessibility in attitude formation.

In short, both frameworks of the MODE model, TRA model, and TPB model share the same idea that there may exists a connection between overall evaluation of an object and a specific evaluation of a specific aspect of that object. The MODE model assumed that the connection might be strong if the overall evaluation, in the form of an association between the attitude object and evaluations of its attributes, has become chronic in memory. The TRA and TPB model, on the other hand, argued that the strength of the connection depends on both the accessibility of the beliefs about the outcomes of the behavior and how the differences in the overall evaluation are associated with the differences in these beliefs.

2.4. The New Ecological Paradigm

In this section, we discuss the theoretical issues related to the New Environmental Paradigm (NEP) (Dunlap and Van Liere, 1978) and its revised version, the New Ecological Paradigm (the revised NEP) (Dunlap et al., 2000), a special type of general attitude designated as one of our focuses in this dissertation. Although this paradigm can be treated as a general attitude, i.e. general attitudes toward environmental problems, its measurement issues require special discussions. As NEP is a special form of environmentalism, this section starts by tracing back to the origin of environmentalism. Then, how the efforts in defining environmentalism led to the introduction of the NEP scale followed.

The Dominant Social Paradigm (DSP) was one of the earliest concepts related to environmentalism. The concept DSP, defined by Milbrath (1989) as a social belief on the functioning of the world around people, was introduced at time when the consumption lifestyle dominated the Western contemporary societies, particularly in the period after the world war II. The consumption ideology, motivated by the belief in the power of industrialization, was thought to shape people's behaviors toward environment. In the view of DSP, thus, consumerism is one barrier to pro-environmental behaviors.

Despite the dominance of anti-environmental DSP, some other motivations for engaging in pro-environmental behaviors received interests from the researchers. The Logic of Collective Action (Olson, 1965) might be a helpful starting point for understanding why people engage in pro-environmental behaviors. The logic in the Olson's theory was summarized by Marwell and Oliver (1993) that 'only irrational motives can explain collective action'. This can be translated into the implication that pro-environmental behaviors are mainly caused by irrational motives, i.e. people behave environmentally without considering their personal benefits. On the other hand, pro-environmental behaviors are among group of prosocial aggression behaviors, which refers to behaviors that are morally acceptable by the society such as altruistic, sympathy, and cooperative behaviors (Wispe, 1972). Hedonic senses of social and material rewards were thought to be one of the motivations for these voluntary behaviors, although some questions were raised regarding whether people voluntarily engage into these behaviors for social outcomes or their behaviors are simply compliances (Schwartz, 1977). This suggested that people perform pro-environmental behaviors not completely in a voluntary way but on purpose, i.e. for social reward motives.

Schwartz (1977) then introduced the norm-activation model of altruism based on the central idea that altruistic behaviors develop causally from moral obligation to act on one's personally held norms. In this notion, pro-environmental behaviors result from altruism and the necessary condition for the implements is the awareness of the environmental consequence. Schwartz's theory of altruism was employed in a number of later studies later in assuming altruistic motivations as determinants of environmentally behaviors (Widegren, 1998). While the altruistic motivations refer mainly to one's orientation toward the welfares of others, Stern et al. (1993) argued that orientations toward biospheric values (e.g., adverse consequences for non-human species) and egoistic values (e.g., adverse consequences for the self) also motivate pro-environmental behaviors. These two additional environmental motivations were then employed by Stern et al. (1993) in expanding Schwartz's theory of altruism. Specifically, the environmental Motivation (M) was assumed to be a function of the Awareness of EGOistic Consequence, AC_{ego}, the Awareness of SOCial-altruistic Consequence, AC_{soc}, and the Awareness of BIOspheric Consequence, AC_{bio} each multiplied with the corresponding weights of V_{ego}, V_{soc}, and V_{bio}, respectively,

$$M=V_{ego}AC_{ego}+V_{soc}AC_{soc}+V_{bio}AC_{bio} \tag{2}$$

The NEP scale marked a milestone in the history of environmental studies. Dunlap and Van Liere (1978) noticed the emergence of several new ways of thinking about the human in relation with the earth that could not be captured by the traditional DSP. The NEP scale was then introduced with 12 items tapping three facets of environmentalism: limits to growth, balance of nature, and anti-anthropocentrism. While the notion of DSP suggested consumerism as a barrier toward pro-environmental behaviors, the idea of NEP on the other hand posited that the new world view may promote pro-environmental behaviors. Interestingly, Stern et al. (1995a) by using data from a northen Virginia sample found that NEP scale is indistinguishable from a scale of awareness of consequence that was used in both Schwartz's theory of altruism and in Stern et al. (1993).

The items of the NEP scale were tested in surveys conducted in the United States, and possible answers for each question included "Strongly Agree", "Mildly Agree", "Mildly Disagree", and "Strongly Disagree" arranged in both negative and positive formats. Overall assessments revealed a high acceptance rate of the new view on environmental problems among both environmentalists and general public which implicitly confirmed the existence of this new way of thinking. The validity, reliability, and uni-dimensionality of the scale were evaluated using four analyses: a corrected item-total correlation test, a Cron-bach's Alpha test, a factor analysis, and principal factor analysis, all with acceptable results. Further, a comparison between the acceptance of the scale by the environmentalist group and general public group showed expected result with higher acceptance level being found in the former group. Similar results were found when several groups defined by social-demographic characteristics (e.g., age, education, and political ideology) were compared.

To adapt the NEP scale with the latest trends in the world view on environmental problems, and to improve its design (e.g., better balance between positive and negative items and reduced bias in the language used), Dunlap et al. (2000) introduced a revision to the NEP scale. The revised NEP scale was termed ‘the new ecological paradigm scale’, which slightly differs from the NEP scale by changing the word ‘environmental’ to ‘ecological’. This fact implies a change in the focus of the revised NEP scale from environmental problems to ecological problems. The revised NEP thus captured some new facets of ecological issues, such as exemptionalism and ecocrisis to form a set of total 15 items. The details of the 15 items in the revised NEP scale were showed in Table 4 and Table 17. In addition, the revised NEP scaled was developed with acknowledging the issues related to the uni-dimensionality of the NEP scale. The fact is that, although the original NEP scale was designed aiming at a single factor representing for one’s belief about environmental problems, a series of later studies suggested that it is in fact composed of several distinct dimensions ranging from one to above four factors in each studies (Dunlap et al., 2000). In the development of the revised NEP scale, again, factor analysis conducted using data of 676 completed questionnaires collected in Washington State highly suggested the existence of one factor representing for all 15 items. However, the authors suggested future studies to consider their specific factor analysis results (e.g., due to the use of different data and contextual factors) before deciding the dimensionality of the ecological worldview. This multidimensionality issue of the revised NEP scale was examined and tested in Amburgey and Thoman (2012). A series of confirmatory factor analysis with different structural models conducted using data from 328 students in the University of Utah concluded that the revised NEP scale is best described as a multifaceted measure of environmentalism.

To date, the NEP scale and its later extended version were the most common measurement for environmentalism (Amburgey and Thoman, 2012; Stern et al., 1995). They are used mainly by psychologists but also by political scientists, sociologists, and geographers with the overall widespread acceptance of ecological beliefs both in the United States and in Europe (Lundmark, 2007). The widely use of the scales, however, went together with criticism, such as on the failure to consider more recent and complex understanding on environmental issues (Lalonde and Jackson, 2002), on their high dependence on the context of the United States and the literature in the late 1960s and 1970s (Lundmark, 2007), on the (generally) weak effects of environmentalism on behaviors (Dunlap, 2008), and unsuitability outside Western countries (Chatterjee, 2008).

2.5. Conclusions

In this chapter, we have addressed several issues related to our central object of general attitudes on this dissertation. Attitudes have a complex structure, not only in the formation, interactions between their elements, and quantifiable and highly abstract characteristics, but their unpredictability and changing natures also make it not straightforward to get insights into them. Our general conclusion from investigating the MODE model and the theories of reasoned behaviors is that general attitudes influence later behaviors mainly through an automatic process where attitude accessibility plays a crucial role. This was in line with our later investigation on the possible relationship between general attitudes and specific attitudes, that the automatic process can influence the interpretations of attitude objects and beliefs about attitude objects. The literature provided various conceptualizations for environmentalism and among them, the latest, most frequently used, and most cited one was the NEP and revised NEP scale. Some criticisms on the NEP scale and the revised NEP scale remained, which are, however, understandable considering their popularity.

Chapter 3: Methodological frameworks

Human behaviors can be defined by a wide range of criteria. Based on decision making processes, behaviors can be volitional actions guided by intentions (Ajzen, 1991; Fishbein and Ajzen, 2009), or behavioral outcomes of automatic self-regulations (Bargh and Chartrand, 1999). Considering the behavioral outcomes, behaviors can be classified into health behaviors, travel behaviors, shopping behaviors, and so on. Behaviors can also be grouped by their frequencies, from daily behaviors, such as commute to work, to infrequent behaviors, such as residential relocations. Similarly, behaviors can have a dichotomous nature, such as voting/not voting, a discrete nature, such as visiting certain restaurants, or a continuous nature, such as the time spending with daily exercise. Jaccard and Blanton (2014) defined behaviors as any overt actions performed by individuals, groups, or living things. Fishbein and Ajzen (2009) noted that each behavior should be viewed in its context. They defined four basic elements of a behavior, including the *action,* the *target* of that action, and the *time* and the *context* where the action takes place.

Travel behaviors generally include various aspects, such as the trip purposes, the trip frequencies, the origin/destination locations, the route choices, the modes used, the departure/arrival times, and other various elements. Our primary interest in travel behaviors in this dissertation was transport mode uses. The use of a given mode can be seen as the outcome of a specific decision making process of the traveler. Roughly, decision making processes can be grouped into compensatory strategies, where information is processed using certain cognitive efforts such as trading-offs, and non-compensatory strategies, where heuristics are used to reduce cognition (Payne et al., 1993; Rothrock and Yin, 2008). Clearly, decision strategies employed in a mode use situation are impossibly observed and, thus, there is no way to be certain on which strategies dominate the travelers in a given situation. Travel behaviors may be consequential in the view of travelers due to their great impacts to the travelers, such as travel time, travel cost, or safety. Such consequences may trigger more traveler's cognitions in mode use decisions. However, travelers may also prefer non-compensatory approaches due to the limitation in cognitive abilities. A number of transport studies have investigated this bounded rationality aspect of travel decisions. For example, the failure of rationality-based theories in accounting for the roles of habits on behaviors has been well acknowledged (Schwanen et al., 2012; Verplanken et al., 1994). Similarly, Ababio-Donkor et al. (2020) found significant impacts of affects, a factor that is hardly understood as representing for a deliberate thinking process, on public transport use behaviors.

Acknowledging that the travelers may adopt various decision rules, we are in favor of a framework that allows integrating various decision processes into explaining behaviors. Among different behavioral models in the literature, we decided to utilize choice models and SEMs. Choice models were extensively employed by economists to understand the choice decisions from a given choice set. Although early forms of the choice model were strongly featured by a trading-off between attributes, advanced choice models now allow understanding the role of irrational motivations behind the choice behaviors. Similarly, SEMs and other covariance techniques were preferred in psychological studies. Whereas representing compensatory aspects of decision making is one among strengths of choice models, SEMs on the other hand offer a more direct way of observing the effects of psychological factors, accounting for non-compensatory decision rules, on behaviors.

In the followings, we first examine several forms of choice models, from basic models to their state-of-the-art, which serve as the frameworks for the case studies in Chapter 4 and Chapter 5. We then present the framework of SEMs that has been applied in the case studies in Chapter 6 and Chapter 7. Frameworks were presented separately following their characteristics, nevertheless they are used flexibly in all of our case studies.

3.1. Choice model framework

Although choice models can cover both discrete choices and/or continuous choices, only the former one were considered in this dissertation. Discrete Choice Models (DCMs) basically include three elements, a *decision maker* who makes a choice from a set of *alternatives* considering alternative's *attributes* (Ben-Akiva and Bierlaire, 1999).

Each of decision makers in DCMs is modeled individually. For this reason, DCMs are also called disaggregate model where individual's choices are modeled separately and then their choices are aggregated. DCMs treat decision makers not as a whole, nevertheless they assume all decision makers to have the same decision rule, which in most cases is *utility maximization* (De Vos et al., 2016). Utility maximization is a problem rooted in macroeconomics where a consumer spends his/her money in a way that maximizes his/her utility. In this notion, alternatives are compared by their utilities. Described in McFadden (2001), the Random Utility Maximization (RUM) model assigns a specific utility part (V) and a random term (ε) to each alternative and the alternative with the maximum (V+ε) will be chosen by the decision maker.

The specific utility (V) of each alternative is conventionally considered to include all utilities brought by its observable (to the analyst) attributes. For example, the specific utility of a mode can be a function of its travel time, which implies the utility by time saving, and travel cost, which similarly implies the utility in terms of cost saving. The socio-demographic characteristics of the decision makers can also be added to the formation of the specific utility (V) in order to account for the heterogeneity of preferences among them (Ben-Akiva and Bierlaire, 1999). All the utilities unobservable to the analyst are included in the error term (ε). This approach gives the analyst freedom in specifying the choice model. All the alternatives available to the decision maker then form the consideration choice set. Under RUM models, different assumptions on the distributions of error terms lead to different models. The most common ones are probit models, derived from assuming that the error terms (ε) follow multivariate normal distributions, logit models, where the error terms follow Gumbel type I distributions, and mixed logit models where the distributions of the error terms (ε) include an arbitrarily specified distribution and another part following Gumbel type I distribution. Among these models, the logit model is the one has a closed-form expression of the probability function, and the shape of the distribution curve of ε is still close to that of normal distribution (Train, 2009). In favor of this valuable property of the logit model, we employed the logit model as kernels for all of our choice models. The following subsections gives specific frameworks built based on this logit kernel that have been applied in case studies in Chapter 4 and Chapter 5.

3.1.1. The logit model

In case studies in Chapter 4 and Chapter 5, we employed the logit model as the kernel from that other advanced models were based. This sub-section thus presents the general framework of the logit model.

The logit model is derived directly from RUM plus the assumption of the error terms as following Gumbel type I distributions. Let us assume that an individual n makes a choice from a choice set of J alternative. The specific part of the utility of the *ith* alternative ($i \subset J$) viewed by individual n, V^{logit}_{in}, is assumed to be a function of its attributes and the individual's socio-demographic characteristics, x_{in}. Let ε_{in} be the stochastic part of the utility of the *ith* alternative, U^{logit}_{in}, then,

$$U_{in}^{logit}=\beta_{0i}+\beta_i x_{in}+\varepsilon_{in}=V_{in}^{logit}+\varepsilon_{in} \quad (3)$$

where β_{0i} and β_i are the intercept for the ith alternative and coefficients that represent the effects of x_{in} on U^{logit}_{in}. The logit model is derived by assuming that all ε_{in}, $(i \subset J)$, are Gumbel type I Independently Identically Distributed (I.I.D). This implies that the logit choice model does not allow for correlated error terms, which is necessary if the analyst wants to model choice behaviors using panel data, or when he/she thinks that certain alternatives in the choice set may correlate. The latter case was illustrated in the well-known red-bus–blue-bus paradox in mode choice modeling. The distribution density function of the error term of the ith alternative viewed by individual n, $f(\varepsilon_{in})$ are,

$$f(\varepsilon_{in})=e^{-\varepsilon_{in}}e^{-e^{\varepsilon_{in}}} \tag{4}$$

The probability that the ith alternative is chosen by individual n under RUM, after several algebraic manipulations (Train, 2009), is

$$P_n^{logit}(i)=Prob(U_{in}^{logit}>U_{jn}^{logit})\forall i\neq j = Prob(V_{in}^{logit}-V_{jn}^{logit}+\varepsilon_{in}>\varepsilon_{jn})\forall i\neq j$$

$$=\int\left(\prod_{j\neq i} e^{-e^{-(V_{in}^{logit}-V_{jn}^{logit}+\varepsilon_{in})}}\right)e^{-\varepsilon_{in}}e^{-e^{\varepsilon_{in}}}d\varepsilon_{in}=\frac{e^{V_{in}^{logit}}}{\sum_{j\in J} e^{V_{jn}^{logit}}} \tag{5}$$

The most common method for estimating the logit choice model is Maximum Likelihood Estimation (MLE) method. Applying MLE for the logit choice model, the likelihood function $L^{logit}(\theta)$ with parameters being estimated θ for a sample of N individual is,

$$L^{logit}(\theta)=\prod_{n\in N}\prod_{i\in J}P_n^{logit}(i)^{di.n} \tag{6}$$

where di.n is a dummy variable that takes the value of 1 if individual n chose alternative i and 0 otherwise, and the log-likelihood function $LL^{logit}(\theta)$, that is more convenient for estimation, is,

$$LL^{logit}(\theta)=\sum_{n\in N}\sum_{i\in J}(di.n)\log P_n^{logit}(i) \tag{7}$$

Maximizing $L^{logit}(\theta)$, equivalent to solve for the equation $LL^{logit}(\theta) = 0$, yields the estimates of parameters θ from which the analyst can make hypotheses about factors that influence choices. The goodness-of-fit of the logit model can be evaluated by the Likelihood Ratio Index LRI = $1 - LL^{logit}(\hat{\theta})/LL^{logit}(0)$, where $LL^{logit}(\hat{\theta})$ is the final loglikelihood of the fitted model and $LL^{logit}(0)$ is that of the model without coefficients. The value of LRI ranges from zero, i.e. the estimated model is no better than 'no model', to one, i.e. the choices of the sample are perfectly predicted.

3.1.2. The error component logit mixture model

In the case study in Chapter 4, we used panel data (e.g., repeated trips). It is expected that choice behaviors of the same person in several trips correlate with each other. The logit model is thus unsuitable for this type of data. To allow correlated choices, specifically correlated utilities, an error component was introduced into the logit model to account for the correlations over repeated choices. The new model is commonly called the error component logit mixture model. Eq. 3 now becomes,

$$U_{in}^{err\_comp} = \beta_{0i} + \beta_i x_{in} + \xi_{in} + \varepsilon_{in} = V_{in}^{err\_comp} + \varepsilon_{in} \tag{8}$$

where ξ_{in} is the error component of $U^{err\_comp}{}_{in}$ assumed to be normally distributed over individuals and not observations (ξ_{in} is fixed for the same mode i in the repeated choices of the same person n and, hence, standing for the correlation between sequence of choices of that alternative); $U^{err\_comp}{}_{in}$ and $V^{err\_comp}{}_{in}$ are utility and specific part of utility of mode i viewed by individual n in the error component logit mixture model.

Whereas Eq. 4 is similar to those of the logit model with only the label 'logit' be replaced by 'err_comp', the need to integrate the probability functions over the distribution of ξ_{in} leads Eq. 5 to,

$$P_n^{err\_comp}(i) = \int \frac{e^{V_{in}^{err\_comp}}}{\sum_{j \in J} e^{V_{jn}^{err\_comp}}} \frac{1}{\sigma_\xi \sqrt{2\pi}} e^{-\frac{1}{2}\left(\frac{\xi_{in}}{\sigma_\xi}\right)^2} d\xi_{in} \tag{9}$$

where σ_ξ is the variance of ξ_{in}. By denoting a single parameter σ_ξ representing for the variance of ξ_{in}, the model implicitly assumes that all individuals in the sample have the same correlation parameter for their repeated choices of a certain mode. The error component logit mixture model now can be estimated using Eq. 6, and Eq. 7.

3.1.3. The integrated choice and latent variable model

In the logit model, all the unobserved utilities of a mode are represented in its single error term ε. This makes the model unable to distinguish between the contributions of various unobserved factors on the mode utilities. For example, a person may use buses instead of cars in certain trips partly due to his/her positive attitude toward environment. Because this attitude is not directly measured, its effects on mode utilities are merged with the effects of other unobserved factors to form a single error term ε. The needs to consider the effects of unobservable factors, or latent variables, on alternative utilities gave rise to the ICLV models (Ben-Akiva et al., 2002).

In ICLV models, latent variables that represent factors not directly observed are assumed to directly cause mode utilities. By formulating latent variables to have the same role as other exploratory variables in the utility functions, the analyst implicitly treats these variables as forms of 'utility' to the decision makers that are not captured by exploratory variables. By definition, latent variables are abstract constructs that can only be revealed through their indicators. In practice, the analyst can integrate these indicators into choice models directly, through measurement equations (Ben-Akiva et al., 2002), or through latent variable structural model (Walker and Ben-Akiva, 2002). In the followings, we present the frameworks of the third approach which was applied in case studies in Chapter 4 and Chapter 5. Specifically, we first considered a standard framework of ICLV model, which is applicable for cross-sectional data and for the case that the attitudinal indicators are considered continuous variables. We then introduced the modified ICLV model to consider panel data (e.g., correlated choice data) and categorical attitudinal indicators. The standard ICLV model and the modified ICLV model were applied in case studies in Chapter 5 and Chapter 4, respectively.

The standard ICLV model

The standard ICLV model was designed for being used with cross-sectional data, continuous indicators, and sequential estimation method[6]. Let x^*_{mn} be the m*th* ($m \subset M$) latent variable, such as a psychological factor, that contributes to mode utilities of individual n, and z_{kmn} ($k \subset K$) be its k*th* indicator. In the utility functions, the analyst can integrate as many latent variables as he/she desires.

The structural equations of the standard ICLV model represent the effects of socio-demographic variables and other latent variables on a latent variable. For x^*_{mn}, the structural equation is,

$$x^*_{mn} = \lambda_{0m} + \lambda_m x_n + \sum_{k \neq m} \lambda^*_{km} x^*_{kn} + \omega_{mn} \quad (10)$$

where x_n denote socio-demographic characteristics of individual n that cause x^*_{mn}; x^*_{kn} denotes k*th* latent variable in the model assumed to cause the m*th* latent variable x^*_{mn}; ω_{mn} is the error terms of x^*_{mn}, assumed to be normally distributed; λ_m and λ^*_{km} are coefficients that represent the effects of x_n and other latent variables on x^*_{mn}, respectively; λ_{0m} is the intercept for x^*_{mn}. The measurement equation for z_{kmn} is,

[6] In the sequential estimation method, the structural equations and measurement equations are first estimated in order to calculate the scores of latent variables. These estimated scores are then inputted directly into the utility functions. Finally, the choice models are estimated conditioned on those estimated scores of latent variables.

$$z_{kmn}=\beta_{0km}+\beta_{km}x^{*}_{mn}+\varepsilon_{kmn} \tag{11}$$

where β_{km} is the correlation between z_{kmn} and x^{*}_{mn}; β_{0km} is the intercept for z_{kmn}; ε_{kmn} is the error term for z_{kmn}, assumed to be normally distributed. In this dissertation, we designated the Likert scale with five levels (e.g., from 1 to 5) for all the attitudinal questions used in measuring general and specific attitudes. In the standard ICLV model, the indicators were treated as continuous variables. Their raw scores from the questionnaires thus can enter Eq. 11 directly. The utility function for mode i viewed by individual n is,

$$U_{in}^{ICLV\_standard}=\beta_{0i}+\beta_{i}x_{in}+\sum_{m\subset M}\beta^{*}_{mi}x^{*}_{mn}+\varepsilon_{in}=V_{in}^{ICLV\_standard}+\varepsilon_{in} \tag{12}$$

where β^{*}_{mi} is the coefficient that represents the effect of x^{*}_{mn} on $U^{ICLV\_standard}_{in}$ and other notations follow Eq. 3. In Eq. 12, the latent variables enter the utility functions as similar to other exploratory variables because the standard ICLV model employs the sequential estimation approach. The random aspect of latent variables is thus not considered. Their predicted scores are derived from estimating SEMs[7] using Eq. 10 and Eq. 11, and then are directly inputted into the utility functions. The probability that mode i is chosen by individual n is:

$$P_{n}^{ICLV\_standard}(i)=\frac{e^{V_{in}^{ICLV\_standard}}}{\sum_{j\in J}e^{V_{jn}^{ICLV\_standard}}} \tag{13}$$

The likelihood function for the standard ICLV model with a sample of N individuals is,

$$L^{ICLV\_standard}(\beta)=\prod_{n\in N}\prod_{i\subset J}P_{n}^{ICLV\_standard}(i)^{di.n} \tag{14}$$

The modified ICLV model

In this case, we treated the attitudinal indicators as categorical variables with five possible discrete values (e.g., from 1 to 5) and additional error terms were added to Eq. 12 to account for correlations between repeated choices. In addition, the simultaneous estimation method was applied for the modified ICLV model. In this estimation method, the choice model, the structural model, and the measurement model are simultaneously estimated by using a joint probability function derived from multiplying individual probability functions of psychological indicators and choice model.

We start developing the framework of the modified ICLV model by considering structural and measurement equations. Both Eq. 10 and Eq. 11 hold in the modified ICLV model. For the

[7] See Sub-section 3.2 for the framework and estimation method of SEM.

categorization of indicators, we assume that there exist 4 thresholds τ_1 ,.., τ_4 for each (continuous) latent variable so that 5 corresponding intervals can be defined. The assumption underlying this approach is that the respondent will choose a specific answer for an attitudinal question (i.e., the answer number "3") if his/her attitude falls into the corresponding interval (i.e., the [τ_2 - τ_3] interval). An example of this approach was given in Figure 10. Thus, the probability that individual n gives the answer $l \subset L = [1 ,.., 5]$ to the question of the k*th* indicator of the m*th* latent variable x^*_{mn} conditioned on the distribution of the (error terms of) latent variables x^*_{mn} is:

$$P_n(l.k|\omega_{mn})=P\left(\tau_{l-1}\leq z_{kmn}\leq\tau_l\right)=\Phi\left(\frac{\tau_l-\beta_{0km}-\beta_{km}x^*_{mn}}{var(\varepsilon_{kmn})}\right)-\Phi\left(\frac{\tau_{l-1}-\beta_{0km}-\beta_{km}x^*_{mn}}{var(\varepsilon_{kmn})}\right) \quad (15)$$

where Φ is the CDF of the normal distribution and var(ε_{kmn}) is the variance of ε_{kmn}.

Similar to the standard ICLV model, the utility functions in the modified ICLV model treat latent variables as similar as other exploratory variables. However, the scores of these latent variables are not prior estimated. Instead, the latent variables remain their random nature in the utility functions. The utility function for mode i viewed by individual n in the modified ICLV model is,

$$U_{in}^{ICLV\_modified}=\beta_{0i}+\beta_i x_{in}+\sum_{m\subset M}\beta^*_{mi}x^*_{mn}+\xi_{in}+\varepsilon_{in}=V_{in}^{ICLV\_modified}+\varepsilon_{in} \quad (16)$$

where ξ_{in} is defined as similar to that in Eq. 8. The probability that mode i is chosen by individual n conditioned on the distribution of the (error terms of) latent variables x^*_{mn} and the correlation element ξ_{in}, is:

$$P_n^{ICLV\_modified}\left(i|\omega_{mn,m\subset M};\xi_{in}\right)=\frac{e^{V_{in}^{ICLV\_modified}}}{\sum_{j\in J}e^{V_{jn}^{ICLV\_modified}}} \quad (17)$$

The joint probability of observing both the mode choice and attitudinal answers by individual n given the distribution of stochastic components embedded in the individual probability functions is,

$$\mathcal{L}_n^{ICLV\_modified}\left(\omega_{mn,m\subset M};\xi_{in}\right)=$$

$$\prod_{i\subset J}P_n^{ICLV\_modified}\left(i|\omega_{mn,m\subset M};\xi_{in}\right)^{di.n}\prod_{m\subset M}\prod_{k\subset K}\prod_{l\subset L}P_n(l.k|\omega_{mn})^{dl.km.n} \quad (18)$$

where dl.km.n takes the value of 1/0 corresponding with the n*th* individual chose the l*th* answer to the k*th* indicator of the m*th* latent variable. Integrating this conditional probability over the distribution spaces of the stochastic components yields the unconditional probability of observing the mode choice and attitudinal choices of individual n,

$$\mathcal{L}_{\mathrm{n}}^{\mathrm{ICLV\_modified}} = \iint_{\omega_{\mathrm{n}};\xi_{\mathrm{in}}=-\infty}^{+\infty} \mathcal{L}_{n}^{\mathrm{ICLV\_modified}}(\omega_{\mathrm{mn,m}\subset \mathrm{M}};\xi_{\mathrm{in}})\mathrm{d}(\omega_{\mathrm{mn,m}\subset \mathrm{M}};\xi_{\mathrm{in}}) \tag{19}$$

Finally, the likelihood function for the modified ICLV model with a sample of N individuals is,

$$\mathrm{L}^{\mathrm{ICLV\_modified}}(\beta) = \prod_{\mathrm{n}\in\mathrm{N}} \mathcal{L}_{\mathrm{n}}^{\mathrm{ICLV\_modified}} \tag{20}$$

3.1.4. The latent class choice model

Another way of investigating the effects of latent variables on mode choice is through LCC models or latent segmentation models. The primary issue with traditional choice models (and ICLV models) is to account for heterogeneity (Gopinath, 1995; Hess, 2014; Hess et al., 2011), and LCC models offer an alternative way of heterogeneity treatment (Greene and Hensher, 2013) in addition to the commonly used mixed logit models (Hess, 2014). Basically, LCC models assume that individuals can be internally segmented into latent classes that have different taste parameters (Hess, 2014). The assignment of an individual to a specific class is specified by a membership model and this is where latent variables can play a role. Specifically, instead of formulating the class membership probabilities to be constants (Kamakura and Russell, 1989) or to be caused by socio-demographic variables (Atasoy et al., 2013; Gupta and Chintagunta, 1994; Hess et al., 2013; Hurtubia et al., 2014; Walker and Li, 2007), the analyst can assume that latent variables are determinants of latent class segmentations (Gopinath, 1995; Hosoda, 1999; Motoaki and Daziano, 2015; Yazdanpanah and Hosseinlou, 2016a). In this dissertation, we assumed that individuals can be grouped into *two latent classes that differ in taste parameters and which class they are placed in depends on their attitudes*. In this LCC model framework, choice models are estimated separately for two classes resulting in the two discrete sets of estimates. We did not attempt to find the optimal number of classes because this issue falls out of the main purpose of this dissertation. In fact, Hess (2014) mentioned that specifying the class number is still an unsolved problem for choice models. In addition, increasing the class number will make (parametric) choice models difficult to estimate and, hence, leading to unstable estimates. This is more serious when latent variables are included that requires additional integrals in the estimation process. While a LCC model with two classes is enough for examining our postulated effects, and considering the trade-off between the benefit in terms of more heterogeneity considered and the reduced model stability when more classes are considered, we decided to hypothesize the existence of two separate classes in our LCC framework. A similar reasoning can be found in Hurtubia et al., (2014).

This sub-section thus presents the framework of the LCC model assuming that there exist two latent classes in the sample. This framework based on the logit kernel and allowed for use with panel data and categorical attitudinal indicators. Traditionally, the LCC model includes of a membership model to specify class assignments, and a separate choice model for each class. We assume that an individual n can be placed into one of the two classes, namely Class 1 and Class 2 (the class base). As the classes are latent to the analyst, the class assignments can be specified by a probabilistic approach. Commonly, logit form is used for modeling the class probabilities (Hess, 2014; Yazdanpanah and Hosseinlou, 2016b). Applying this practice, the probability that individual n belongs to Class 1 (relative to Class 2) conditioned on his/her attitudes x^*_n (and hence, the error terms ω_n)[8] is given as,

$$\pi_{n,C=1}(\omega_n)=\frac{e^{\delta_1+\tau x^*_n}}{1+e^{\delta_1+\tau x^*_n}} \tag{21}$$

where δ_1 is the constant of the membership model for Class 1 (the corresponding constant for Class 2 is set at zero); τ represents the effect of attitudes x^*_n on the probability of falling into Class 1 and; C=1 denotes Class 1 (An estimated *positive* value of τ indicates that an increase in the level of x^*_n will lead to higher probability of being in *Class 1*, and vice versa for the negative value of τ). In addition, the determination of the attitudes x^*_n and their categorical indicators follows Eq. 10, Eq. 11, and Eq. 15. The specific choice model for each class has the same form as in Eq. 16 with the only exception that a class label is added. Thus, the utility of mode i viewed by individual n belonging to Class C $\subset$ [C1; C2] is,

$$U^C_{in}=\beta^C_{0i}+\beta^C_i x_{in}+\xi_n+\varepsilon^C_{in}=V^C_{in}+\varepsilon^C_{in} \tag{22}$$

where ξ_n denotes the correlations between repeated choices of the same individual n[9], and V^C_{in} is the specific part of utility of mode i viewed by individual n in class C and conditioned on the value of ξ_n. The probability that mode i is chosen by individual n, conditioned on Class C and a given value of ξ_n, is:

[8] This section differs from Section 3.1.3 where we denote x^*_n and ω_n as a representation for multiple latent variables (e.g., two attitudes in this case) and their corresponding error terms, for the sake of simplicity.

[9] Due to the complexity of the estimation for LCC model, the coefficients representing for the correlations between alternatives in repeated choices of the same individual in the LCC framework are constrained to be equal over all the alternatives. In terms of parametric models, this is different from the ICLV framework where fewer number of model parameters allows for assuming the correlations in repeated choices to vary among alternatives.

$$P_n^{LCC}(i|C;\xi_n)=\frac{e^{V_{in}^C}}{\sum_{j\in J} e^{V_{jn}^C}} \tag{23}$$

The probability that individual n choose mode i conditioned on the value of ξ_n is the average of the probabilities of his/her choices under two classes weighted by the corresponding class probabilities,

$$P_n^{LCC}(i|\xi_n)=\sum_{C=1}^{2}\pi_{n,C}\prod_{i\subset J}P_n^{LCC}(i|C;\xi_n)^{di.n} \tag{24}$$

The joint probability of observing both mode choice and attitudinal choices of individual n conditioned on ω_n and ξ_n is,

$$\mathcal{L}_n^{LCC}(\omega_n;\xi_n)=\prod_{i\subset J}P_n^{LCC}(i|\xi_n)^{di.n}\prod_{k\subset K}\left[\prod_{l\subset L}P_n(l.k|\omega_n)^{dl.k.n}\right]=$$

$$\left\{\sum_{C=1}^{2}\pi_{n,C}\prod_{i\subset J}P_n^{LCC}(i|C;\xi_n)^{di.n}\right\}\left\{\prod_{k\subset K}\left[\prod_{l\subset L}P_n(l.k|\omega_n)^{dl.k.n}\right]\right\} \tag{25}$$

Similar to the ICLV model, integrating the conditional likelihood in Eq. 25 results in the unconditional probability of observing all the mode choice and attitudinal choices of individual n under LCC model,

$$\mathcal{L}_n^{LCC}=\iint_{\omega_n,\xi_n=-\infty}^{+\infty}\mathcal{L}_n^{LCC}(\omega_n;\xi_n)d(\omega_n;\xi_n) \tag{26}$$

Finally, the likelihood function for the LCC model with a sample of N individuals is,

$$L^{LCC}(\beta)=\prod_{n\in N}\mathcal{L}_n^{LCC} \tag{27}$$

3.1.5. Bias correction method for binary choice model

When mode share patterns are strongly skewed towards certain modes (e.g., dominating modes, such as car), the observed choices for other modes (e.g., dominated modes, such as bus) become "rarer." The very low mode shares of some alternatives relative to the others can cause choice data to be separated[10] at certain levels (Frischknecht et al., 2014). In such cases, choice models can be subject to bias in the estimates and convergence problems (Bull et al., 2007; Heinze, 2006; Rainey, 2016). Particularly in a binary choice model, the situation of extremely low ratio of choices of one mode over those of the remaining mode is similar to a rare event in logistic regression[11]. In logistic regression, it is quite common to observe that the use of a small sample size, sparse, unbalanced, or highly stratified data may lead to data

[10] Data separation can happen when one independent variable, or a combination of several independent variables, perfectly or nearly perfectly predicts the dependent variable.
[11] The binary logit model with the assumption that the error terms of the utility functions are Gumbel type I distributed is equivalent to a logistic regression model.

separation and large bias in the estimates (Heinze, 2006; Mehta and Patel, 1995). In such situations, the confidence intervals of the estimates are not trusted (Heinze, 2006). This fact, thus, suggests that the binary choice data should be checked first for separation, and if such separation exists, corrections should be applied. This issue happens to various choice models, including ICLV models, that use highly unbalanced mode share data. In this dissertation, the case study in Chapter 5 used choice data in a rural area where car use dominated bus use and, hence, being more prone to data separation. In the followings, we first demonstrate how data separation causes unreliable estimates and estimation convergence problems in logistic regression, which also applies to the binary logit model. We then propose one solution to correct the biases and to improve the stabilities of the estimates that the binary logit model with highly unbalanced mode share patterns may face. The proposed approach was applied to correct for bias in the estimates in case study in Chapter 5.

Data separation problem

Albert and Anderson (1984) defined data separation as the situation when observations can be allocated completely to or nearly completely to groups by a group membership vector. Given a sample of observations characterized by (p+1) variables $x^T = (x_0, x_1, \ldots, x_p)$, where the letter 'T' denotes transposing, and each observation belongs to only one among the g groups $H_1, \ldots, H_g$, complete separation is said to happen in the data if there exists g vectors $(\alpha_1, \ldots, \alpha_g)$ of (p+1) dimensions corresponding to g groups so that for any observation i in the group H_j ($j \in g$) and for $j, t \in g$ ($j \neq t$),

$$(\alpha_j - \alpha_t)^T x_i > 0 \tag{28}$$

where x_i is the *ith* realization of x^T. In the absence of complete separation, quasi-complete separation occurs if,

$$(\alpha_j - \alpha_t)^T x_i \geq 0 \tag{29}$$

and the equality exists for at least one observation in each group. For illustration, let us consider a simple binary logistic model of bus choice event with the dependent variable y of bus choice (y takes 1/0 corresponding with bus is chosen/not chosen) predicted by an intercept $x_0 = 1$ and one independent variable x_1 of being student (x_1 takes 1/0 corresponding with the respondent is a student/not a student). Given a sample of 7 observations, three possible cases of y and x_1 distributions are depicted in Figure 7.

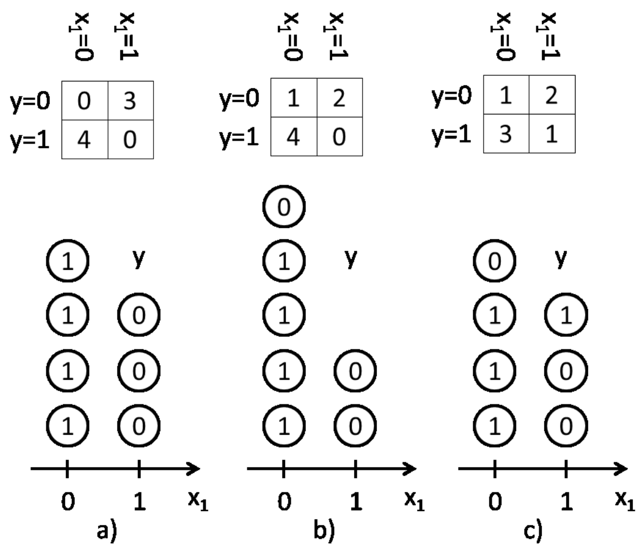

Figure 7. Three cases of distributions of bus choice observations and the corresponding two-way contingency tables.

Note: Number 1 and 0 in circle denote bus chosen (y=1) and bus unchosen (y=0), respectively; a) Completely separated: all bus choice observations are allocated on the value of $x_1=0$ and all non-bus choice observations are allocated on the value of $x_1=1$; b) Partially overlapped: overlap happens to the value $x_1=0$; c) Completely overlapped on all values of x_1.

In the first case a), complete separation happens because the variable x_1 completely allocate 7 observations into two separate groups (e.g., Group 1 consists of all bus choice observations and Group 2 of all non-bus choice observations). The corresponding two-way contingency table thus exhibits two zero-cells. The second case b) shows an example of quasi-complete separation as both bus choice and non-bus choice observations overlap on the value $x_1=0$, and hence, one zero-cell still exists in the corresponding two-way contingency table. The last case is a normal case where overlaps happen on both values of x_1, and thus making non-zero cells in the two-way contingency table. See Appendix. A for the proof of the existence of data separation/non-separation in the three cases.

The problem of data separation mainly occurs to categorical data (Menard, 2002). In the examples above, if the predictor is a continuous variable (e.g., considering now the time-to-the-nearest-bus-stop variable), their wider range of values (e.g., from zero to more than 50 minutes) may reduce the possibility of separating the bus choice observations from non-bus choice observations. In fact, the above examples imply a problem with the rarity of bus choice rather than with the model. That is, the special case of observing all the students not choosing bus may only happen in a particular sample due to randomness in the data collection procedure, and not in the population.

When data separation occurs, Albert and Anderson (1984) proved that maximum likelihood estimates of the logistic regression model do not exist (e.g., being unbounded). In the data separation examples above, the parameter for x_1 will go to infinity because the observed odds ratio of bus choice to non-bus choice of student group ($x_1 = 1$) is zero. Thus, the model will converge without maximum likelihood estimates. This is in line with Allison (2008)'s finding that maximum likelihood estimates do not exist whenever there is one zero cell in the two-way contingency table.

Bias correction method for binary logit model with highly unbalanced mode share patterns

There are several methods for dealing with data separation in the literature. Brathwaite and Walker (2018) suggested that in such situations, relaxing the implicit assumption of symmetry propert[12] of the probability function by employing asymmetric probability function potentially leads to better explanation for the observed choices. One immediate solution for data separation is to avoid it, such as to transform/omit the variables that cause separations or to use a different model (e.g., the linear regression model) (Allison, 2008; Heinze, 2006). Removing some explanatory variables while they are related to the dependent variable for example, has been strongly criticized, as it will deliberately accepts specification bias (Rainey, 2016; Zorn, 2005). In case the analyst prefers the logistic regression model, solutions that can correct the estimates for biases caused by data separation are more desirable. One of the early approaches to data separation is to employ exact logistic regression (Cox and Snell, 1989). Unlike the conventional logistic regression model, the likelihood function maximizes the likelihood of observing the exact p-values for the null hypothesis that each parameter β_r ($r \in 0, 1, \ldots, p$) in the probability function of the logistic regression model is equal zero, conditioned on the observed values of all other predictors. These p-values are calculated based on the observed sufficient statistics (e.g., the sufficient statistic for β_r is $t_r = \sum_{i=1}^{N} y_i x_{ir}$) and the permutations of the data rather than large-sample chi-square approximations, and thus basically remaining unaffected by data separation problems (Allison, 2008). This approach, however, becomes very computationally intensive with large sample sizes, many predictors and/or continuous predictors (Frischknecht et al., 2014). A more compromising solution is to apply Firth (1993) bias correction method. This method is initially proposed not to deal with data separation but to reduce the bias in the logistic regression estimates by penalizing the

[12] An implicit assumption in the multinomial logit (MNL) and binary models is that from the middle point where an alternative has the probability of being chosen of 50%, increasing or decreasing the value of an attribute by the same amount will result in the same changes (in magnitude) in the probability of that alternative.

model likelihood function. However, Heinze and Schemper (2002) showed that Firth method is an ideal solution to the data separation problem in the binary logistic regression model, and Bull et al. (2002) extended this method to the multinomial logistic regression model. The framework of Firth method is simple and many statistical software packages include Firth method as an option to the users. In the followings, we show how Firth method works in a binary logistic regression framework. The idea here is that because the binary logit model is equivalent to the logistic regression model, Firth method is thus applicable to the binary logit model. Other methods for data separation can be found in (Frischknecht et al., 2014; Kosmidis and Firth, 2011; Zahid and Heumann, 2012).

The proposed framework here is to view binary logit choice model as the logistic regression model where Firth bias correction method can be applied. Thus, the formulae of the (binary) logit model will be first re-written in the form of the binary logistic regression model. Then Firth method is applicable afterward. Considering now a binary logit model (Then number of alternatives J=2), Eq. 5 and Eq. 3 are re-written as follow,

$$P_n^{logit}(i)=\frac{e^{V_{in}^{logit}}}{\sum_{j\in(J=2)} e^{V_{jn}^{logit}}}=\frac{1}{1+e^{-(V_{in}^{logit}-V_{jn}^{logit})}}=\frac{1}{1+e^{-(\beta_{0i}+\beta_i X_{in}-\beta_{0j}+\beta_j X_{jn})}}=f(\beta) \tag{30}$$

where i and j denote two alternatives in the binary choice set. The probability function of the alternative i over the alternative j in the binary choice set written in this way is exactly the probability function of the logistic regression model[13],

$$P_n^{logistic}=\frac{1}{1+e^{-(\beta_0 x_{n0}+\beta_1 x_{n1}+\cdots+\beta_p x_{np})}} \tag{31}$$

where $P_n^{logistic}$ denotes the probability of the event/occurrence in the n*th* observation of the total N observations corresponding to N individuals in the sample, and β_0, β_1, … β_p are (p+1) parameters for (p+1) predictors x_{n0}, x_{n1}, … x_{np} with $x_{n0}\equiv 1$. The likelihood function for the logistic regression model represented by Eq. 31 is,

$$L^{logistic}(\beta)=\prod_{n=1}^{N}\left[\left(P_n^{logistic}\right)^{y_n}*(1-P_n^{logistic})^{1-y_n}\right] \tag{32}$$

where β denotes parameters to be estimated and y_n takes value 1 if the event occurred and 0 vice versa. The maximum likelihood estimate for r*th* parameter $\hat{\beta}_r$ (r ∈ 0, 1, …, p) of β_r is derived from solving the r*th* score equation,

[13] The logistic regression model assumes that the ratio of the probability of the event/occurrence to the non-event/non-occurrence (the odds ration) is a function of a linear combination of the predictors and an intercept: $\log[p_n/(1-p_n)] = \beta_0 + \beta_1 x_{n1} + \ldots + \beta_p x_{np}$. A modification of this basic equation leads to Eq. 31.

$$U(\beta_r)=\frac{\partial \log L^{logistic}(\beta)}{\partial \beta_r}=\sum_{n=1}^{N}\left(y_n\text{-}P_n^{logistic}\right)x_{nr}=0 \tag{33}$$

Due to a finite number of observations, $\hat{\beta}_r$ is always biased from the true values β_r, and the asymptotic bias can be written as (Firth, 1993),

$$\text{bias}(\beta_r)=\frac{b_1(\beta_r)}{N}+\frac{b_2(\beta_r)}{N^2}+\cdots, \tag{34}$$

where $b_1(\beta r)$, $b_2(\beta r)$ … are the first-order bias, second-order bias, … of β_r and N is the number of observations in the sample. Firth (1993) proved that for exponential family, penalizing $L^{logistic}(\beta)$ by multiplying it with a small bias $|i(\beta)|^{\frac{1}{2}}$, the square root of the determinant of the Fisher information matrix of $L^{logistic}(\beta)$, can lead to the elimination of the first order bias $b_1(\beta)/N$ of $\hat{\beta}$. Let $L^{*logistic}(\beta)=L^{logistic}(\beta)|i(\beta)|^{\frac{1}{2}}$ be the modified likelihood function of $L^{logistic}(\beta)$, and let $U^*(\beta_r)$ be the bias-corrected score function for β_r, then Eq. 33 becomes (Firth, 1993; Heinze and Schemper, 2002),

$$U^*(\beta_r)=\frac{\partial \log L^{*logistic}(\beta)}{\partial \beta_r}=U(\beta_r)+\frac{1}{2|i(\beta)|}\frac{\partial |i(\beta)|}{\partial \beta_r}=\sum_{n=1}^{N}\left[y_n-P_n^{logistic}+h_n\left(\frac{1}{2}-P_n^{logistic}\right)\right]x_{nr}=$$
$$\sum_{n=1}^{N}\left[(y_n-P_n^{logistic})x_{nr}\left(1+\frac{h_n}{2}\right)\right]+\sum_{n=1}^{N}\left[(1-y_n-P_n^{logistic})x_{nr}\frac{h_n}{2}\right]=0 \tag{35}$$

where $i(\beta)=X^TWX$ is the Fisher information matrix of the binary logistic regression model with the Nx(p+1) design matrix X including N observations of (p + 1) explanatory variables x_r ($r \in 0, 1, \ldots, p$) and the NxN diagonal matrix $W=\text{diag}\{P_n^{logistic}*(1-P_n^{logistic})\}$; h_n is the n*th* diagonal element of the matrix $H=W^{1/2}X(X^TWX)^{-1}X^TW^{1/2}$. Compared with Eq. 33, each n*th* original observation of (y_n; x_{nr}) is split into two observations (y_n; x_{nr}) and ($1\text{-}y_n$; x_{nr}) with the corresponding weights of $(1+h_n/2)$ and $h_n/2$. As any value of x_{nr} has been associated with both an event and a non-event (e.g., y_n and $1\text{-}y_n$), this ensures the overlaps of all possible values of y (1 and 0) on all the predictors x_{nr}. As a result, all the cells of the two-way contingency table are modified so that non-zero cells are eliminated. In the special case of a single binomial observation (y_n) with n=1, the method is equivalent to adding ½ to y_n (Firth, 1993)[14]. As the estimates of the logistic regression model are generally biased from zero under finite samples (Copas, 1988), Firth method helps correct the biases by shrinking the estimates toward zero and, thus, yielding more accurate estimates. In addition, the modified score function in Eq. 35 can be used in a normal iteration process to estimate β_r and to derive its standard error. The

[14] Rewriting Eq. 35 to $U^*(\beta_r)=\sum_{n=1}^{N}\left[\left(y_n+\frac{h_n}{2}\right)-(1+h_n)p_n\right]x_{nr}$ one can easily see that Firth method is equivalent to add $h_n/2$ to y_n and h_n to 1. For a single binomial observation model, $h_1=1$, the modification becomes equivalent to adding ½ to y_1, a common method for bias reduction in logistic regression (Firth, 1993; Zorn, 2005).

data separation problem is thus solved for the binary logistic regression model and, hence, being applicable to the binary logit model.

3.2. Structural equation model framework

Beside choice models, SEMs were another useful analysis tool for behavioral studies. SEMs were introduced to sociology in 1960s (Bollen and Noble, 2011), and now have become a popular analyzing technique in various fields. SEMs were mostly applied in psychology, sociology, the biological sciences, educational research, political science, and market research (Golob, 2003). SEMs are well known for their ability to consider latent variables, such as social constructs, through a measurement model. This distinguishing feature makes SEMs suitable for analyzing latent determinants of travel behaviors that this dissertation attempted.

Unlike conventional statistical analyzing techniques, such as regression models and Analysis of variance (ANOVA) where individual observations are focused, the frameworks in SEMs are covariance based. Fundamentally, SEMs assume a parametric model with the covariance structure represented by $\Sigma(\theta)$, and then find a set of parameters θ so that,

$$\Sigma(\theta) = \Sigma \tag{36}$$

where Σ is the covariance structure observed in the sample or population (Bollen, 1989). The model implied covariance matrix $\Sigma(\theta)$ contains relationships assumed in the model. Basically, any SEM employs a measurement model for representing the relationships between latent variables and their indicators, and a structural model that relates these latent variables with each other. A common approach in developing the measurement model in SEMs is to employ an exploratory analysis (e.g., a factor analysis or a principal component analysis). In the followings, we first present the framework of Principal Component Analysis (PCA), which supports developing our SEM specifications. Then, the SEM framework is followed.

3.2.1. Principle Component Analysis

A crucial assumption in SEMs is that the latent variables, such as some concepts, cognitive processes, or social phenomena, do *exist* but are unobservable (to the analyst). The assumption of the existence of latent constructs necessitates another assumption, that these constructs manifest in some observable facts. For example, in constructing the 12 items for the NEP scale (Dunlap and Van Liere, 1978), the authors argued that new environmental ideas against traditional DSP have something in common and they termed these new ideas as “New Environmental Paradigm”. In this case, the authors assumed that the “New Environmental Paradigm” does exist among people, and this latent construct can be indirectly measured through specific 12 items. The first step of developing measurement models for SEMs is thus selecting indicators for the latent variables. A common procedure for the selection of the indicators of latent variables, which is also applied in this dissertation, is: (1) Designing the questionnaire forms with question items aiming at measuring the target constructs; (2) Conducting the surveys using these questionnaire forms to get the respondent data and; (3) Deciding the final set of items for each construct based on exploratory analyses. The last step in this procedure is necessary as it allows the analyst to see how well pre-designated items measure the same construct, from that he/she can excludes irrelevant items to improve the measurement model. PCA is one among available approaches for that.

To start with PCA, let's consider a sample of N individuals characterized by p attitudinal indicators $(x_1,x_2,\dots,x_p)$ intended for measuring several attitudes in question. Each indicator x_r ($r \in 1,2, \dots, p$) can be considered a random variable with N observations corresponding to the responses of N individuals $(x_{1r},x_{2r},\dots,x_{Nr})$ for the r*th* indicator. Let $X' = (x_1,x_2,\dots,x_p)$ be a p-elements vector contains p random variables $(x_1,x_2,\dots,x_p)$ having covariance matrix Σ (In case of using a sample, Σ is replaced by S), where $'$ denotes transposing. The purpose of PCA is to find linear combinations of $(x_1,x_2,\dots,x_p)$ (the components) that have maximum variances. Clearly, any set of p transformations can represent the data completely. The idea of PCA, however, is to use a smaller number of components (the principle components) to represent the data without much loss of variation. To do so, consider now p vectors of p dimensions $a_r = (a_{r1},a_{r2},\dots,a_{rp})$, $r \in 1,2, \dots, p$ consisted of constants. The original vector X can be linearly transformed into a new vector by multiplying its elements $(x_1,x_2,\dots,x_p)$ with p elements contained in each a_r. The principle of PCA is to find p orthogonal vectors $(a_1,a_2,\dots,a_p)$ so that the first transformation $a_1'X$ has the largest variance (the first component), the second transformation of a'_2X has the second largest variance (the second component), and so on. By doing so, vectors $(a_1,a_2,\dots,a_p)$ serve as coordinators where the original data are viewed at different levels of variation. Consider now the vector $a_1'X$ as the first transformation of X,

$$a_1'X=a_{11}x_1+a_{12}x_2+\dots+a_{1p}x_p \tag{37}$$

The variance of this first transformation, $(a_1'\Sigma a_1)$, can only be maximized if some constraints are put on a_1. Consider a constraint that a_1 be having an unit length, equivalent to $a_1'a_1=1$. Now we can find a_1 by using Lagrange multipliers in maximizing the expression $a_1'\Sigma a_1-\lambda_1(a_1'a_1-1)$. Take a differentiation of this expression with respect to a_1 yields the equation,

$$\Sigma a_1 - \lambda_1 a_1 = 0 \leftrightarrow (\Sigma - \lambda_1 I) a_1 = 0 \qquad (38)$$

where λ_1 and I are the Lagrange multiplier for a_1 and the identity matrix, respectively. By the definition of eigenvector and eigenvalue, the solution to Eq. 38 yields the result that a_1 and λ_1 be any of pairs of eigenvector and eigenvalue of Σ, respectively. Additionally, the variance of the transformation to be maximized is,

$$\mathrm{Var}(a_1'X) = a_1'\Sigma a_1 = a_1'\lambda_1 a_1 = \lambda_1 a_1' a_1 = \lambda_1 \qquad (39)$$

This implies that a_1 is the eigenvector associated with the largest eigenvalue of Σ. For the second, third, and remaining vectors, employing the same maximization process plus the condition that these vectors are orthogonal yields the result that all p vectors $(a_1,a_2,\ldots,a_p)$ correspond to p eigenvectors $(e_1,e_2,\ldots,e_p)$ of Σ, and the associated p eigenvalues $(\lambda_1, \lambda_2,\ldots, \lambda_p)$ show the extents to which they can account for the covariance of X (Jolliffe, 2002). Based on the distribution of eigenvalues, the analyst then can select the number of principal components to be retained and interpret them as the constructs being measured.

Denote Z as the vector consisted of p principal components of X. From the above result, we have,

$$Z = A'X \qquad (40)$$

where $A' = (e_1,e_2,\ldots,e_p)$ denotes the matrix consisted of p eigenvectors of Σ. The k*th* element of Z (e.g., k*th* principal component) is given as,

$$Z_k = e_k'X = (e_{k1}x_1 + e_{k2}x_2 + \ldots + e_{kp}x_p) \qquad (41)$$

where $(e_{k1},e_{k2},\ldots,e_{kp})$ are p elements of the k*th* eigenvector of Σ. The covariance between k*th* principal component Z_k and r*th* indicator x_r now becomes,

$$\mathrm{Cov}(Z_k,x_r) = (e_{k1}x_1 + e_{k2}x_2 + \ldots + e_{kp}x_p)x_r = e_k' \begin{bmatrix} x_1x_r \\ x_2x_r \\ \ldots \\ x_px_r \end{bmatrix} \qquad (42)$$

Let's $\alpha' = (0,0,\ldots,1,0,\ldots,0)$ is vector that has all elements being zero and only r*th* element being 1, then,

$$\begin{bmatrix} x_1x_r \\ x_2x_r \\ \ldots \\ x_px_r \end{bmatrix} = \begin{bmatrix} x_1x_1 & x_1x_2 & \ldots & x_1x_r & \ldots & x_1x_p \\ x_2x_1 & x_2x_2 & \ldots & x_2x_r & \ldots & x_2x_p \\ \ldots & \ldots & \ldots & \ldots & \ldots & \ldots \\ x_px_1 & x_px_2 & \ldots & x_px_r & \ldots & x_px_p \end{bmatrix} \alpha = \Sigma\alpha \qquad (43)$$

Thus Eq. 42 becomes,

$$\mathrm{Cov}(Z_k,x_r)=e_k'(\Sigma\alpha)=(e_k'\Sigma)\alpha=(\Sigma e_k)'\alpha=(\lambda_k e_k)'\alpha=\lambda_k(e_k'\alpha)=\lambda_k e_{kr} \quad (44)$$

due to associativity property of matrix multiplication (e.g., A(BC) = (AB)C), the symmetry form of Σ (e.g., $e_k'\Sigma=(\Sigma e_k)'$), the property of eigenvectors (e.g., $\Sigma e_k=\lambda_k e_k$), and e_{kr} denotes the r*th* element of k*th* eigenvector e_k of Σ. The correlation between the k*th* principal component Z_k and r*th* indicator x_r, generally called the factor loading, is calculated straightforward,

$$\mathrm{Corr}(Z_k,x_r)=\frac{\mathrm{Cov}(Z_k,x_r)}{\sqrt{\mathrm{Var}(Z_k)}\sqrt{\mathrm{Var}(x_r)}}=\frac{\lambda_k e_{kr}}{\sqrt{\lambda_k}\sqrt{\mathrm{Var}(x_r)}}=\frac{\sqrt{\lambda_k}e_{kr}}{\sqrt{\mathrm{Var}(x_r)}} \quad (45)$$

with $\mathrm{Var}(Z_k) = \sqrt{\lambda_k}$ (e.g., from Eq. 39) and $\mathrm{Var}(x_r)$ denotes the variance of x_r.

The factor loadings represent the correlation between the principal components (the factors) and indicators. In most cases, a rotation solution can help to interpret the factor loading patterns easier. In this dissertation, we employ the VARIMAX rotation for PCA in case of two and above factors retained. The principle of VARIMAX is to orthogonally rotate the factor loading matrix by multiplying it with a rotation matrix. After the rotation, the original factor loadings are re-distributed in a way that the VARIance of factor loadings of each factor is MAXimized. By this, the interpretation of the factors is made easier (e.g, each factor will have only a few large factor loadings). In addition to looking at the factor loading patterns, the Cronbach's alpha (see (Kline, 2011) for the alpha formulation) provides another evaluation method for the internal consistency of each factor with higher values of alphas are desired.

3.2.2. Structural equation model

If PCA provides the analyst a method for selecting appropriate indicators for a factor from an original set of indicators, the Confirmatory Factor Analysis (CFA) on the other hand verifies, or confirms, the validity and reliability of the measurement model as part of SEM specifications (e.g., it allows for correlations between indicators and uses the same covariance-based method as in SEMs). In fact, CFA is more inclined to a confirmation approach. It requires a model to be pre-specified, including how many latent variables, or which indicators belong to which latent variable, and so on, and then the estimation result shows how good the indicators measure their assigned latent variables. A CFA model is, in fact, special case of SEMs. Because a CFA model aims at verifying how well the indicators measure the intended latent variables, it becomes a sub-system of SEMs dedicated for dealing with measurements. Thus, SEMs basically include a CFA model and a structural model. In practice, CFA is commonly embedded in SEMs but can still be used separately. For this reason, this sub-section presents the general framework for both CFA model and SEMs.

Model specification

The notation used in this section followed Bollen (1989) and Bollen and Noble (2011). An example of a CFA model with two latent variables and three indicators for each is given in Figure 8, while an example of a SEM with one exogenous latent variable and two endogenous latent variables, each with three indicators, is given in Figure 9. Both figures are for illustration purpose but cover all types of relationship in CFA models and SEMs in our case studies. In these figures, one-way dashed arrows represent measurement relations, one-way solid arrows represent one-way causal effects, and two-way headed arrows represent correlations. In addition, rectangles denote observed variables and ovals represent latent variables. Figure 8 is quite a standard CFA model, whereas we added some more complex relationships in Figure 9, such as correlated disturbances (e.g., between ζ_1 and ζ_2) and reciprocal relationships (e.g., between η_1 and η_2).

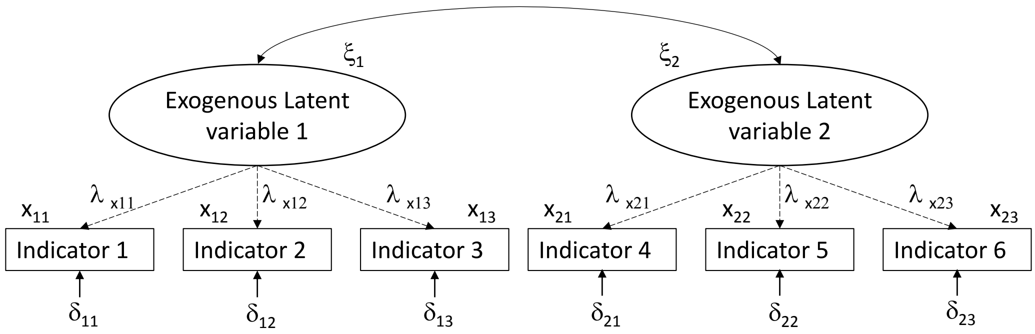

Figure 8. An example of a CFA model.

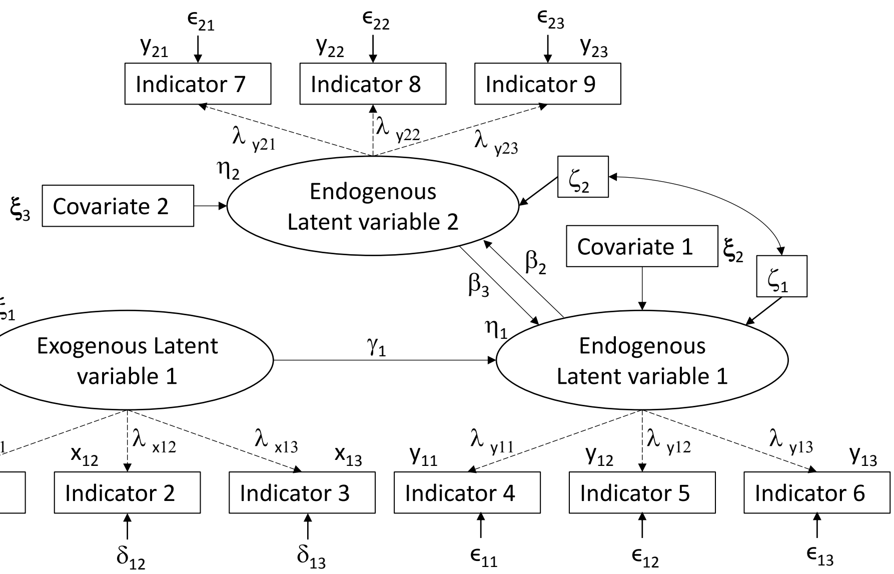

Figure 9. An example of a SEM.

Whereas CFA includes only measurement equations, SEMs instead include both measurement equations and structural equations. As a common practice, we define a variable as exogenous variable if it is not caused by any other variables in the model, and as endogenous variable if it is caused by at least one other variable in the model. In both CFA and SEMs, the measurement equations relate latent variables with their indicators,

$$x=\lambda_x\xi+\delta \tag{46}$$

$$y=\lambda_y\eta+\epsilon \tag{47}$$

where x and y are indicators of exogenous latent variables ξ and endogenous latent variables η with factor loadings λ_x and λ_y and error terms δ and ϵ, respectively. In a CFA model, all latent variables are considered exogenous, thus Eq. 47 is not applicable. In SEMs, the structural equations relate latent variables with their determinants,

$$\eta=\beta\eta+\gamma\xi+\zeta \tag{48}$$

where β and γ are regression coefficients showing the effects of other endogenous latent variables and exogenous variables (e.g., exogenous latent variables and covariates) on endogenous latent variables. The disturbance term ζ only available for endogenous latent variables implies an assumption, that endogenous latent variables are not completely explained by other variables available in the model. The model implied covariance matrix of observed variables can be obtained from Eq. 46, Eq. 47, and Eq. 48 (Bollen, 1989),

$$\Sigma(\theta)=\begin{bmatrix}\Lambda_y\left(\mathrm{I}\text{-}\mathrm{B}\right)^{-1}(\Gamma\Phi\Gamma'+\Psi)^{-1}[\left(\mathrm{I}\text{-}\mathrm{B}\right)^{-1}]'\Lambda'_y+\Theta_\epsilon & \Lambda_y\left(\mathrm{I}\text{-}\mathrm{B}\right)^{-1}\Gamma\Phi\Lambda'_x \\ \Lambda_x\Phi\Gamma'[\left(\mathrm{I}\text{-}\mathrm{B}\right)^{-1}]'\Lambda'_y & \Lambda_x\Phi\Lambda'_x+\Theta_\delta\end{bmatrix} \tag{49}$$

which can be used in Eq. 36 for estimating the model.

Identification

Identification is an important issue in SEMs. Generally, a model is said to be unidentified if there does not exist any solution of θ that satisfies $\Sigma(\theta) = \Sigma$, just identified if there exists only one solution of θ, and over-identified if there are more than one solution of θ. The last case is desired, as the analyst can select the best solution (e.g., the model that best fits the data) from those available, whereas the first two cases may happen for various reasons, typically when the number of indicators per latent variable is small or incorrect specifications. To date, researchers have suggested a number of identification rules, for example T-rule, Two-step rule, and MIMIC rule (Bollen, 1989), using computer algebra systems (Bollen and Bauldry, 2010), dividing SEM into blocks (Rigdon, 1995), and rules for non-recursive models (Kline, 2011).

As identification is generally not a problem when there are several indicators per each latent variable, we specially focused on the issue of latent variables with single indicators. There are at least three approaches for dealing with single-indicator latent variables. The first, and most straightforward way, is to treat these indicators as observed variables, such as in Donald et al. (2014) and Shen and Takeuchi (2001). Another approach is to still use single-indicator latent variables in SEMs but set the variances of the error terms of their indicators at some fixed values (e.g., at 20% of the variances of the observed indicators, which is equivalent to consider the indicators to have the measurement reliability at 80%[15]) in order to make the measurement models (and hence SEMs) identified (Bollen, 1989; Kline, 2011). The last approach is similar to the second approach, but the variance of the error terms of the single indicators are set free. The applicability of the last approach depends on the specification of each model and (to our knowledge) there is not a general rule. In this dissertation, we applied the third approach in the case study in Chapter 7.

Estimation

Eq. 36 forms the basis for model estimation. SEMs can be estimated using various methods which are mainly different according to the assumption of the distributions of observed variables. In this section, we present two methods used in cases studies in Chapter 6 and Chapter 7.

In case the observed variables in SEMs are considered to be normally distributed, the Maximum Likelihood Estimation (MLE) method can be applied. Let z be a vector of (p+q) elements generated by merging p observed variables in x and q observed variables in y successively. z is now multivariate normal distributed with the parameter of $\Sigma(\theta)$. The distribution function of z is given as,

$$f(z;\Sigma(\theta))=2\pi^{-(p+q)/2}|\Sigma|^{-1/2}\exp\left[(-\frac{1}{2})z'\Sigma(\theta)^{-1}z\right] \qquad (50)$$

Given a sample of size N, the likelihood function can be specified based on their joint density function is $f(z_1;z_2;...;z_N;\Sigma)=\prod_{i\in N} f(z_i;\Sigma)$,

$$L(\theta)=2\pi^{-N(p+q)/2}|\Sigma|^{-N/2}\exp\left[(-\frac{1}{2})\sum_{i\in N} z_i'\Sigma(\theta)^{-1}z_i\right] \qquad (51)$$

[15] The score reliability of an indicator Y with the error term E is generally denoted as $r_{YY} = 1 - var(E)/var(Y)$.

and the log-likelihood function is (Bollen, 1989),

$$\log L(\theta)=\frac{-N(p+q)}{2}\log(2\pi)-\frac{N}{2}\log|\Sigma|-\frac{N}{2}\mathrm{tr}\left[S^{*}\Sigma(\theta)^{-1}\right] \quad (52)$$

where S* is the sample covariance matrix with N in the denominator. Maximizing either L(θ) in Eq. 51 or logL(θ) in Eq. 52 yields the MLE parameters θ.

In case the data is not multivariate normally distributed, the model Chi-square and standard errors are likely to be biased although parameter estimates are unaffected (Finney and DiStefano, 2013). In this dissertation, we applied the nonparametric bootstrapping technique to deal with non-normal data in MLE. Described in (Kline, 2011), this method consider the sample as the population and randomizes the cases within the sample to generate as many samples as the analyst wants. Based on the computer generated samples, the standard errors are derived as being equal to the standard deviation of the distribution of the generated samples. This method was applied in the case study in Chapter 7.

Apart from MLE, Muthén (1984) introduced a robust weight least square estimator for SEMs, which has become a common solution for dealing with categorical variables. The method called WLSMV basically treats categorical indicators to have underlying continuous latent variables whose continuous values when falling under certain intervals will result in particular categorical values. Let us consider a simple SEM of a latent variable of "car use" behavior with an indicator of "Car_use_frequency" (e.g., from the case study in Chapter 6), given in Figure 10 with noting that the identification issue is not considered in this model,

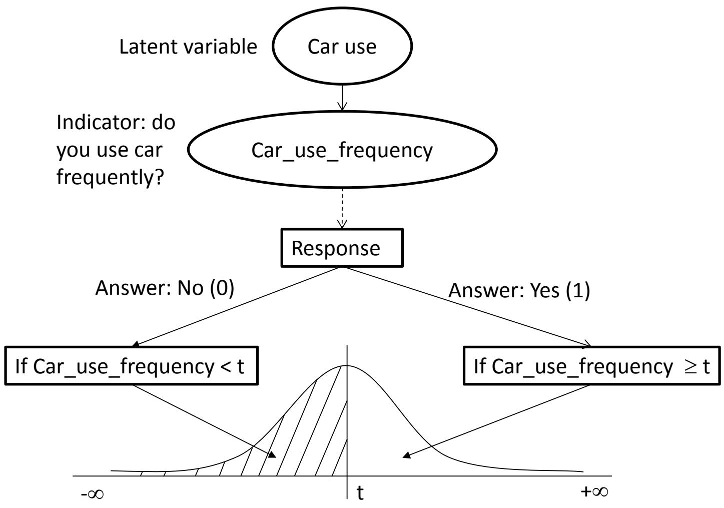

Figure 10. A simple SEM for car use behavior.

Assume that the respondents can select two possible answers of Yes (1) and No (0) for the question “Do you use car frequently”, their categorical (dummy) responses of 1/0 can be assumed to be caused by a latent continuous variable of “Car_use_frequency”. If the value of Car_use_frequency is smaller than a certain threshold t, then the respondents will give the answer 0, and vice versa. This categorization can be extended to considering more thresholds and, hence, more intervals. The model then estimates the threshold t and the polychoric covariances [16] between latent variables underlying each categorical indicator. In SEM estimation using least-squares method, the polychoric covariance matrix will be used instead of normal (Pearson) covariance matrix of continuous indicators. Specifically, the estimation process will minimize the squares of the differences between observed covariance matrix and model implied covariance matrix using the diagonal of the weight matrix. The weight matrix is derived by inversing the asymptotic polychoric covariance matrix. Finally, the full weight matrix is used for calculating the standard errors. This method was use in the case study in Chapter 6.

Model evaluation

The most important test for the overall goodness of fit of SEMs is the chi-square test since it is a fundamental measure of the difference between the observed and implied covariance matrix (Bollen, 1989; Hair, 2010). A good model should show a non-significant chi-square. Because the chi-square statistic by itself is very sensitive to the sample size, in practice, models are nearly always rejected with large sample sizes (Bentler and Bonett, 1980). In an attempt to overcome this dependence on the sample sizes, the root mean square error of approximation (RMSEA) (Steiger & Lind, 1980) has been widely used in a way that both the model complexity (in terms of the number of parameters) and sample size are included in the calculation (Hair, 2010). The acceptable range for the RMSEA, as suggested by Hair, should be between 0.03 and 0.08 at a 95% level of confidence. The goodness-of-fit statistic (GFI) developed by Jöreskog and Sörbom (the general form of the GFI for the case using MLE can be found in (Bollen, 1989; Jöreskog et al., 1996) provides another way to assess the overall model fit. Conventionally, the suggested value for the cut-point of the GFI is 0.9 (Hair, 2010; Hooper, D., Coughlan, J. and Mullen, 2008). The incremental fit is tested by the normed fit index (NFI), with an NFI value larger than 0.9 showing a good model (Bentler and Bonett, 1980), and the comparative fit index (CFI) with a value larger than 0.9 is suggested for a good

[16] Polychoric correlation/covariance is an estimate of correlation/covariance between latent (continuous) variables assumed to underlie categorical indicators. In other words, correlation/covariance between categorical indicators is calculated indirectly through their underlying latent variables.

model (Hair, 2010; Hooper, D., Coughlan, J. and Mullen, 2008). In short, the CFA and SEM were tested by the chi-square χ^2 (together with the degrees of freedom), the RMSEA, the GFI, the NFI, and the CFI.

3.3. Conclusions

In this chapter, the frameworks for choice models and SEMs were given. Whereas choice models are based strongly on RUM in explaining choice behaviors, and appear to be useful for simulating trading-off aspects of decision making processes, SEMs are featured by their background built on the notion of causality and measurements for latent variables. In this sense, SEMs account for non-compensatory aspects of behavioral decisions in a more direct way. In fact, the measurement equations and structural equations in SEMs are used in the frameworks of both ICLV model and LCC model for accounting for latent variables and their indicators, nevertheless they are not estimated using a covariance-based approach as in SEMs. Choice models and SEMs are thus two distinct models that together provide a better solution for explaining behaviors.

Chapter 4: ICLV and LCC framework for examining the effects of environmentalism and APA on mode choice behaviors

4.1. Introduction

In this case study, we explored the potential effects of environmentalism and APA on mode choice behaviors. Among various aspects of travel behaviors, which modes being used by the travelers, collectively, can have a significant impact on various aspects of life, from direct and urgent issues such as congestions, air quality, and accidents, to issues of wider scale, such as planning of shopping store chain and public transport system, to even problems at global scale such as global warming and energy consumption. Analyses of choice behaviors can help answering the issue of demand-supply matching, which is a common issue not only in transport but also in economics. For example, the emergence of car sharing, autonomous cars, and vertical take-off and landing aircrafts recently posed a challenge for the urban planning sectors in predicting the demands for these technologies. The facilitations and regulations for these technologies from governments will depend much on which modes the travelers prefer. Unsurprisingly, mode choice behaviors attracted a large part of the literature on transport studies.

To date, a number of psychological factors have been integrated into mode choice models, such as attitudes and perceptions (Bolduc et al., 2008; Roberts et al., 2018; Temme et al., 2007), personal traits (Paulssen et al., 2014; Vredin Johansson et al., 2006), environmental concerns (Atasoy et al., 2013; Roberts et al., 2018; Sottile et al., 2015a; Vredin Johansson et al., 2006), latent attributes such as modal comfort and convenience (Morikawa et al., 2002; Yáñez et al., 2010), preference for safety, comfort, convenience and flexibility (Paulssen et al., 2014; Temme et al., 2007; Vredin Johansson et al., 2006), and habit (Donald et al., 2014; Idris et al., 2015). However, the effects of environmentalism and APA on mode choice were not well documented. This case study thus aimed at providing another empirical evidence for these effects. Following the frameworks of the modified ICLV model and the LCC model in Chapter 3, we designed a questionnaire for getting mode choice and psychological data from respondents living in Nagoya, Japan. Then, the model estimation results supported our conclusions about the effects of environmentalism and APA on mode choice behaviors.

4.2. Methodological frameworks

To examine the potential effects of environmentalism and APA on mode choice behaviors, we employed both the (modified) ICLV model framework and LCC model framework. Thus, we postulated two corresponding models plus a Base model, which is, in fact, the error component logit mixture model, for comparison. The three models are given in Figure 11.

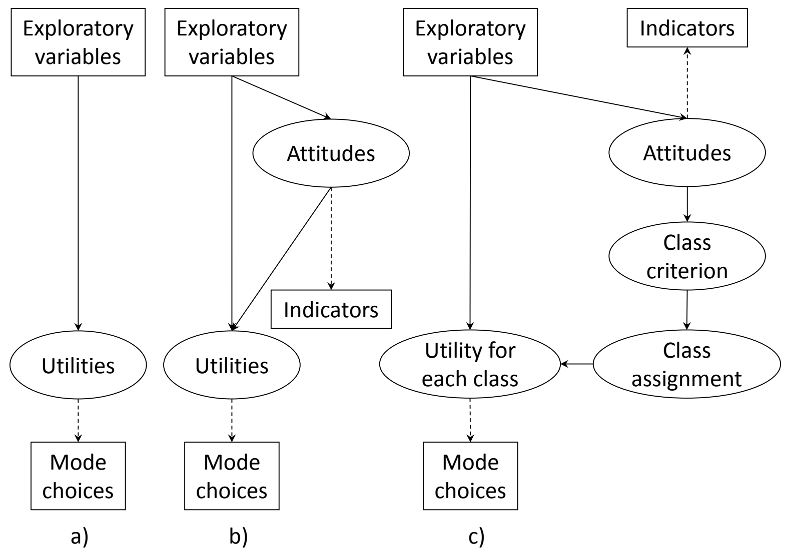

Figure 11. The Base model (a), ICLV model (b) and LCC model (c) for examining effects of environmentalism and APA on mode choice behaviors.

In the ICLV model, the assumption that environmentalism and APA directly cause mode utilities lies at the benefits that the travelers obtain from the acts of choosing a particular mode. As environmentalism is much related to the human's impacts to the ecology system, we assume that the environmental benefit in terms of energy savings by using mass transport is the one motivation for the choice of rail transport. In fact, traveling by rail can be considered a form of pro-environmental behavior[17] (Eriksson, 2008; Poortinga et al., 2004), and the assumption that environmentalism causes rail utility in some sense is similar to the idea adopted by social scientists in 1970s that environmental concerns directly impact environmentally related behaviors (Bamberg, 2003; Maloney and Ward, 1973). For APA, we assume that health benefits brought by doing more physical activity motivate travelers to choose bicycle and walking. In a similar vein, if we expect that environmentalism encourages people to behave more environmentally friendly, then we can also expect that cares for physical activity encourage physically healthy behaviors. In fact, such kind of reasoning has been at least one time employed in the literature, for instance in the study of the influence of physical activity propensity on mode choice (Kamargianni et al., 2015).

In the LCC model, we assumed that people with different attitudes toward environmental issues and physical activity are likely to possess different tastes in their choice behaviors. This

[17] Pro-environmental behaviors are generally defined as any actions that reduce the impacts to the environment or benefit the environment (Steg and Vlek, 2009; Stern, 2000).

assumption stems directly from the basic assumption in ICLV model that environmentalism and APA constituting to some forms of 'utility' to the travelers, such as utilities in terms of health benefits and environmental benefits. The differences in the traveler's environmentalism and APA thus can lead to different evaluations of modes. Conventionally, mode utilities consist mainly of multiplicative forms of mode attributes and the individual's taste parameters. Thus, given the same mode attributes, the different evaluations among travelers can only be explained by the differences in their taste parameters. This creates a theoretical framework for assuming that environmentalism and APA cause different taste patterns, which in the framework of LCC model is translated into different latent classes.

With the above reasoning, the effects of environmentalism and APA on mode choice were tested in two models, an ICLV model and a LCC model. In both models, we designated an error component logit mixture model (the Base model) as the kernel. This enables the use of choice models when repeated choice data is used (e.g., by allowing the repeated choices of the same individual to be correlated).

4.3. Data set

To collect the data for analyzing our proposed models, we hired an e-commerce company in Japan to carry out a web-based survey in Nagoya, Japan in 2018. The company has a rich database of people who have registered at the company's website for online shopping and other activities. The sampling process of the survey followed a quota sample approach. First, individuals in the database of the survey company who are living in Nagoya city and are more than 18 years old are divided into several categories of age and sex. Then within each category, they (e.g., people in the company's database) are randomly selected to be given an invitation to join the web-based survey. The invitations are distributed following the age and sex categories of the population in Nagoya city to ensure that the expected sample will be as much as similar to the Nagoya population in terms of age and sex distribution. The interested individuals were then further screened to ensure that they have car access[18] and have at least three frequent trips longer than 2km. Finally, if all screening questions have been passed, the remained individuals would be allowed to join the main survey. With the above characteristics of the survey, the respondents in our sample are car drivers in Nagoya who were included in the survey company's database. The main survey consists of three parts.

[18] We asked the respondents regarding the number of cars in their household and how often they drive (from "never", "sometimes" and "frequent") to ensure that the screened respondents have car access.

The first and second part of the main survey are designed for collecting individual's characteristics and their self-estimations of some mode attributes, respectively. In the first part, respondents were required to give some basic socio-demographic information, such as age, income, education and so on. Which socio-demographic variables are included in the questionnaire depends on their potential effects on the mode utilities and latent variables hypothesized. For instance, the education level was found to have an effect on environmentalism (Dunlap et al., 2000) and hence being included. The second part is designed to obtain the chosen mode and the self-estimations of mode-related attributes for the available modes in the respondents' three most frequent trips. By using observations from the repeated choices, we expect to get more reliable inferences from the dataset. Respondents could select their three most frequent trips from a given list of up to five trip purposes: (1) work/school; (2) shopping; (3) recreation/outing; (4) picking-up/dropping-off and; (5) hospital. Once a trip is selected, the following eight modes are shown to the respondents, (1) Driver Alone (DA); (2) Shared ride (SH); (3) Taxi (TA); (4) Motorbike (MB); (5) Subway/Train (RAIL); (6) Bus (BUS); (7) Bicycle (BI) and; (8) Walking (WA), for selecting the most frequently used mode. To ensure that the respondents truly had a choice in each trip reported, we explicitly asked them to remove any modes that were unavailable for their trips. Thus, although all the invited respondents have car access, the car alternative can still be excluded from the choice set if they could not use it for their trips due to any reason, such as parking was unavailable. In our raw data, car use was unavailable in 7.7% of the reported trips. After excluding the unavailable modes, the respondents were asked to give their self-estimations for mode attributes of both the chosen and unchosen (available) modes. It must be noted here that the self-reported mode attributes can contain bias due to over/underestimations (Van Exel and Rietveld, 2009). As all the respondents in our study are car drivers, it is more likely that their estimations on the attributes of other modes (e.g., train, bicycle and walking) are biased from the true attributes to some extent[19]. Thus, this bias must be taken into account in interpreting the results from our study. In fact, it was possible to use other map applications (e.g., Google map) to estimate the mode attributes based on the information of the origin/destination of the respondents, and hence leading to more accurate data. However, we would argue that people make mode choices based on their perceived mode attributes, or *representative* attributes,

[19] To assess the extent of overestimations, we compared the self-reported travel times by DA, RAIL and WA in the first trips of 20% of the respondents with those estimated using Google map. On average, these respondents overestimated all the travel times and the amounts of bias in the travel time by DA, RAIL and WA are 31.77%, 36.26%, and 39.57% respectively. In addition, we found no statistically significant differences (at 95% level of confidence) between the means of respondents' overestimations of travel times of chosen modes and unchosen modes.

rather than actual attributes which vary between different actual situations. Even estimations from map applications do contain biases due to a number of contextual factors contributing to the real situations. Thus, the self-reported mode attributes were used for our analysis instead of attributes estimated using map applications. Several common mode attributes were designated in our study, as shown in Table 1.

Table 1. The summary for collected mode attributes in examining the effects of environmentalism and APA on mode choice behaviors

Attribute \ Mode	DA	SH	TA	MB	RAIL	BUS	BI	WA
In-vehicle travel time (minutes)	x	x	x	x	x	x	x	x
Out-vehicle travel time (minutes)					x	x		
Travel cost (JPY)	x		x	x	x	x		
Travel distance (km)	x			x				
Transfers (number)					x	x		

Note: The out-vehicle travel time includes walking time to/from the nearest bus/train station and waiting time between transfers if incurred; The travel costs are adjusted for any financial supports available to the respondents.

The third part of the main survey is dedicated for collecting individuals' assessments regarding ecological issues and physical activity. The 15 original items in English of the revised NEP scale were used to measure individual's environmentalism. Illustrated in Section 2.4, this version of environmentalism scale is suitable for examining how concerns for the most recent issues, i.e. ecological issues, are related to travel mode choice. The 10 questions in English for measuring APA were designed for capturing how important people value the physical activity. We used both socially desirable and undesirable questions in designing the scale for APA in order to mitigate the social desirability bias, one of common sources for bias in social surveys (Edwards, 1957; Nederhof, 1985; Parry and Crossley, 1950). Further, Paulhus (1984) provided interesting evidence that respondents are more socially desirable if they know that their responses would be made public (e.g. the fact that respondents have to provide the name, address and phone number). For this reason, the contact information of the respondents was not collected in an effort to reduce social desirability bias. Finally, all these questions were translated into Japanese by a native Japanese author of this study, and then shown to the respondents randomly. Respondents could choose one out of five possible answers from a five-point Likert scale (Likert, 1932): (1) Strongly Disagree; (2) Mildly disagree; (3) Unsure; (4) Mildly Agree and; (5) Strongly Agree.

With the above settings, the website was open to the potential respondents on 5th November, 2018 and the data collection completed on 29th November, 2018. In total, 900 respondents have completed our online survey and we received data of mode choices and mode attributes of total 2700 trips in addition to the personal information and psychological answers by each respondent. From the observed mode shares in Table 2, the three alternative TA, MB and BUS were found to be rarely chosen by the respondents, and hence leading to the very low observed mode shares.

Table 2. The observed mode shares in the original 2700 trips in examining the effects of environmentalism and APA on mode choice behaviors.

Mode	Number of observed choices	Percentage (%)
Driver Alone (DA)	2038	75.48%
Shared ride (SH)	92	3.41%
Taxi (TA)	1	0.04%
Motorbike (MB)	25	0.93%
Subway/Train (RAIL)	301	11.15%
Bus (BUS)	42	1.56%
Bicycle (BI)	127	4.70%
Walking (WA)	74	2.74%
Total	**2700**	**100**

In the literature, the critically low mode shares of some alternatives *relative* to the mode shares of other modes can cause the data separation phenomenon in choice models (Frischknecht et al., 2014). When data separation exists, estimates from choice models can have extremely large standard errors and models may not converge (Bull et al., 2007). To our knowledge, current treatments for data separation proposed in the literature do not cover mode choice models with latent variables, such as environmentalism and APA. Thus, our analytic choice set includes only four modes DA, RAIL, BI and WA with the total of 1840 eligible trips[20] accounting for nearly 70% of the total of 2700 reported trips. Table 3 shows some characteristics of respondents in the analytic sample.

Table 3. The summary of statistics of the analytic sample in examining the effects of environmentalism and APA on mode choice behaviors.

Socio-demographic statistics	Mean (std)	Trip purpose	%
Age	47.96 (13.52)	Work	20.30%
Sex (male = 1, female = 0)	0.6 (0.49)	Shopping	24.15%
Car number	1.43 (0.69)	Outing	22.85%
Income (10,000 JPY ~ 92.1 USD)	873.95 (3551.15)	Pickup/drop-off	6.30%
Education (number of education years after	6.2 (2.2)	Hospital	3.85%

[20] Eligible trips are ones that: (1) The available modes include at least two alternatives from our analytic choice set of DA, RAIL, BI and WA and; (2) The chosen modes are either DA, RAIL, BI or WA.

junior high school)			
Distance (in minutes) to the nearest train station	10.39 (5.99)	Other	13.78%
Has ever been involved in an accident in the past? (yes = 1, no = 0)	0.7 (0.46)	**Mode share**	**%**
Occupation	**%**	DA	76.14%
Full-time company worker	53.71%	RAIL	13.59%
Full-time public servant	8.04%	BI	6.85%
Student	0.97%	WA	3.42%
Part-time worker	10.84%	**Average travel time**	**Minutes**
Housework	11.21%	DA	20.85
Unemployed	9.26%	RAIL (in-vehicle)	23.84
Other	5.97%	RAIL (out-vehicle)	29.53
Sample size		BI	19.84
Number of respondents	821	WA	22.59
Number of trips (observations)	1840		

*Note: **std**: standard deviation; JPY: Japanese Yen; USD: United States Dollar.*

In general, the analytic sample contains car drivers aged nearly 48 year-olds with a quite balanced gender distribution. The average income of the respondents in the analytic sample is 873.95 JPY, higher than the average income of Nagoya citizens in 2018 at 565,35 JPY[21]. More than half of the travelers are full-time company workers. The mode share pattern underlines the common situation of car dependency in modern cities, with car choice (DA) constitutes to more than three quarters of the total mode choices. We found no great differences between the observed mode shares of respondents in our analytic sample and those in 153,943 trips (with travel distances longer than 2km) of car drivers in Nagoya in the 5th personal trip survey (2011) conducted for Chukyo region, Japan which includes Nagoya city area[22]. The trip purpose statistic reveals that working, shopping and outing are the most common activities in the travelers' frequent trips.

The average scores of the indicators of environmentalism and APA reported by the respondents in the analytic sample are shown in Table 4. For easy interpretation, we reversed the scores of all the socially undesirable indicators so that moving from 1 to 5 in all the analytic scores corresponds to an increase in the positive view on the ecological problems and physical activity. To see the dimensionalities of the indicators, Table 4 was also accompanied by the result of a PCA with VARIMAX rotation. The mean scores of all the items for environmentalism and APA (3.37 and 3.27, respectively) show overall positive attitudes towards ecological problems and physical activity. Looking at some items for environmentalism with the highest mean scores (3.79 and 3.87 for EN5 and EN7 respectively)

[21] This information is reachable at the city website: http://www.city.nagoya.jp/en/page/0000014169.html
[22] Specifically, the observed mode shares calculated from the raw data of the survey showed the pattern of 66.40%, 17.72%, 8.18%, and 7.70% for car, rail, bicycle, and walking respectively. The information related to this survey can be found in the official website: http://www.cbr.mlit.go.jp/kikaku/chukyo-pt/persontrip/p01.html

and lowest ones (2.71, 2.68 and 2.65 for EN4, EN6 and EN14 respectively), it appears that *respondents in our analytic sample strongly recognize the consequences of human's activities to the earth, but at the same time, still believe in human ability to make use of natural resources in a sustainable way*. These two inconsistent ways of thinking are in line with the existence of two separate factors in the PCA's results. Specifically, Factor 1 that loads highly on items EN1, EN3, EN5, EN7, EN9, EN11, EN13 and EN15 includes the items with the highest mean scores and all the items that Factor 4 highly loads on (EN4 and EN6) are among items with the lowest mean scores. For the indicators of APA, the overall trend is clearer as respondents generally show positive attitudes toward physical activity. Only two items APA8 and APA10 show the mean scores lower than 3 (2.86 and 2.89, respectively) but the departures are insignificant. The fact that respondents' attitudes towards ecological problems show both socially desirable (e.g., by Factor 1) and undesirable (e.g., by Factor 4) ways of thinking whereas their attitudes towards physical activity generally converge to a positive view on the role of physical activity to physical health has an interesting implication. In case where people consider ecological problems, people may (or have to) think about human's growth. The fact is that, promoting for human's growth will require more natural resources to be consumed. This conflict between the two interests may result in different viewpoints on the ecological problems. This fact, however, does not exist in the case of interests in doing physical activity as there are no benefit conflicts.

Table 4. The modified average scores of the indicators and factor loadings from PCA's result (run with modified scores) with 4 factors identified in examining the effects of environmentalism and APA on mode choice behaviors

		Mean (sd)	Factor 1	Factor 2	Factor 3	Factor 4
EN1	We are approaching the limit of the number of people the earth can support	3.47 (0.83)	**0.61**			
EN2*	Humans have the right to modify the natural environment to suit their needs	3.28 (0.99)			0.67	
EN3	When humans interfere with nature it often produces disastrous consequences	3.36 (0.84)	**0.65**			
EN4*	Human ingenuity will insure that we do NOT make the earth unlivable	2.71 (0.83)				0.58
EN5	Humans are severely abusing the environment	3.79 (0.8)	**0.76**			
EN6*	The earth has plenty of natural resources if we just learn how to develop them	2.68 (0.85)				0.56
EN7	Plants and animals have as much right as humans to exist	3.87 (0.88)	**0.52**			
EN8*	The balance of nature is strong enough to cope with the impacts of modern industrial nations	3.32 (0.92)			0.55	
EN9	Despite our special abilities humans are still subject to the laws of nature	3.76 (0.94)	**0.53**			
EN10*	The so-called "ecological crisis" facing	3.11			0.58	

		Mean (sd)	Factor 1	Factor 2	Factor 3	Factor 4
	humankind has been greatly exaggerated	(0.78)				
EN11	The earth is like a spaceship with very limited room and resources	3.61 (0.86)	**0.6**			
EN12*	Humans were meant to rule over the rest of nature	3.73 (0.98)			0.7	
EN13	The balance of nature is very delicate and easily upset	3.68 (0.84)	**0.66**			
EN14*	Humans will eventually learn enough about how nature works to be able to control it	2.65 (0.8)				
EN15	If things continue on their present course, we will soon experience a major ecological catastrophe	3.55 (0.86)	**0.66**			
APA1	Physical activities are important for my daily life	3.64 (0.91)		**0.64**		
APA2*	I do NOT like doing daily exercises	3.08 (1.08)		**0.62**		
APA3	Doing daily exercise helps to prevent diseases and obesity	3.99 (0.83)				-0.67
APA4*	Spare time should be spent for other important works rather than for physical activities	3.06 (0.74)			0.59	
APA5	I always feel comfortable and healthy when doing exercises	3.59 (0.83)		0.41		-0.56
APA6	The Ministry of Health, Labour and Welfare suggested people to follow the "+10" rule: An additional 10 minutes of physical activity per day. Do you agree with the "+10" rule?	3.46 (0.76)				-0.54
APA7	Given I'm busy or not, I always try to do exercises as much as possible	3.04 (0.97)		**0.81**		
APA8	I often make use of any spare minutes to do exercises instead of using mobile phone or other things	2.86 (0.9)		**0.74**		
APA9	I often give advices for my close people such as children, spouse, relative and close friends regarding the importance of physical activities for health	3.06 (0.9)		**0.66**		
APA10	If I have time, I will participate in the campaigns for raising awareness of people about the importance of physical activity for daily life	2.89 (0.94)		**0.66**		

Note: The asterisk symbol "" means the indicator's scores have been reversed; The factor loadings with absolute values lower than 0.4 are not shown; The factor loadings of the indicators that will be used later for measuring environmentalism and APA are marked in* ***bold****; The cut point of eigenvalue of 1 is used for deciding the number of factors retained.*

Based on the result in Table 4 and the followed discussions, we decided to employ the set of indicators EN1, EN3, EN5, EN7, EN9, EN11, EN13 and EN15 for measuring environmentalism, and the set of indicators APA1, APA2, APA7, APA8, APA9 and APA10 for the measurement of APA. By this, we explicitly treat Factor 1 and Factor 2 that have the highest eigenvalues (5.11 and 3.49 respectively) as the representatives for the two construct environmentalism and APA. Apart from the advantage of having the highest eigenvalues that imply the greatest abilities to reproduce the variance of the data, all the items that Factor 1 highly loaded on are items pre-designed for environmentalism, and all the items that Factor 2 highly loaded on are items pre-designed for APA. This fact, however, does not hold for the case of applying Factor 3 or Factor 4 for environmentalism and Factor 4 for APA. The items that Factor 3 and Factor 4 highly loaded on are mixtures of items pre-designed for both environmentalism and APA. This is equivalent to saying that Factor 3 and Factor 4 reflect both environmentalism and APA, and hence being unable to distinguish between these constructs. Thus, while the data alone suggests that all the factors identified in the PCA's results in Table 4 can be used for representing environmentalism and APA, the meanings or implications of items restrict the range of suitable factors to only Factor 1 and Factor 2. In addition, we excluded the item APA5 from the set of indicators for APA as this indicator showed a cross-loading.

4.4. Estimation result

The free package Biogeme (Bierlaire, 2016) was used for the model estimation. The Monte-Carlo integration with Modified Latin Hypercube Sampling (MHLS) (Hess et al., 2006) method for drawing from a standard normal distribution was used for the approximation of the likelihood function (Bierlaire, 2015). In the Base model and the ICLV model, we set the number of draws for the error terms of latent variables and the error component of the utility function that account for the correlated choices for approximating all the integrals at 10,000. Similarly, the number of draws for the error component of the utility function in the LCC model was set at 10,000.

The estimates of the choice models of the Base model, ICLV model and LCC model (DA is set to be the reference alternative) are shown in Table 5. The estimates of the structural models for EN and APA are shown in Appendix B. Due to the biases in the self-reported mode attributes, the estimates of the parameters corresponding to these attributes may differ if the true values of attributes are used. All the socio-demographic variables were coded as dichotomous variables whereas the variables for mode attributes were coded as continuous variables with suitable scaling. Due to the complexity of the LCC model, the parameters of two classes in the LCC model were constrained to differ only in the intercepts and mode attributes. In addition, as the predicted mode share of WA for individuals in Class 2 is nearly zero[23], we excluded WA from the choice set of the individuals in Class 2. The set of

[23] In fact, we tried to estimate the LCC model with WA being included in the choice set of individuals in Class 2. However, some estimates related to WA, such as the intercept and the coefficient of travel time by WA, were found as extremely high. We also found that the mode share predicted for WA in Class 2 was nearly zero, which

parameters for Class 2 is thus different (e.g., less than) from that of Class 1. Although the final log-likelihoods of the ICLV model and LCC model were smaller than that of the Base model as a result of adding the attitudinal choices into the likelihood functions, which implies reductions in the mode choice predictabilities, the value of using these models lies at the explanations for behaviors rather than predictions for choice outcomes (Vij and Walker, 2016).

Table 5. Estimates of Base model, ICLV model and LCC model in examining the effects of environmentalism and APA on mode choice behaviors.

	Base model		ICLV model		LCC model	
	Estimate	t-test	Estimate	t-test	Estimate	t-test
Intercepts						
BI	-2.57	-5.12	-2.47	-4.78		
RAIL	-2.36	-6.51	-2.32	-6.09		
WA	-5.20	-5.38	-5.96	-4.79		
BI^{C1}					-1.49	-3.57
$RAIL^{C1}$					-2.12	-4.47
WA^{C1}					-1.61	-4.27
BI^{C2}					-10.30	-2.23
$RAIL^{C2}$					-3.92	-4.13
Mode attributes						
Travel distance by DA	2.72	2.26	2.68	2.27		
Travel cost	-3.91	-5.73	-3.78	-5.86		
Travel time by DA	-5.23	-5.58	-5.16	-5.61		
Out-vehicle travel time by RAIL	-2.44	-3.77	-2.41	-3.76		
Travel time by BI	-6.59	-6.25	-6.50	-6.33		
Travel time by WA	-7.94	-5.14	-7.77	-5.32		
Number of transfers for RAIL	-4.69	-3.26	-4.56	-3.23		
Travel cost^{C1}					-1.53	-1.72
Travel time by DA^{C1}					-1.06	-1.03[(a)]
Out-vehicle travel time by $RAIL^{C1}$					-3.40	-3.26
Travel time by BI^{C1}					-5.11	-5.37
Travel time by WA^{C1}					-5.27	-5.65
Travel cost^{C2}					-32.60	-3.96
Travel time by DA^{C2}					-10.30	-2.30
Out-vehicle travel time by $RAIL^{C2}$					-5.26	-1.61a
Travel time by BI^{C2}					-16.40	-1.03[(a)]
Socio-demographic characteristics						
Accident_yes_BI	-1.13	-2.93	-1.16	-3.04	-0.70	-2.36
Accident_yes_RAIL	-0.70	-2.60	-0.65	-2.47	-0.67	-2.28
Company_staff_RAIL	0.49	1.76	0.50	1.81	0.48	1.54[(a)]
High_edu_RAIL	1.12	3.54	1.10	3.58	0.93	2.73
Male_BI	1.34	3.05	1.34	3.07	0.80	2.55
Part_time_job_RAIL	0.76	1.66	0.78	1.74	0.84	1.86
Company_staff_BI	-0.75	-1.80	-0.78	-1.87	-0.29	-0.91[(a)]
Unemployed_BI	-1.84	-2.23	-1.76	-2.21	-0.73	-1.19[(a)]
Attitudes						
Effect of EN on RAIL			-0.03	-0.13[(a)]		
Effect of APA on BI			-0.01	-0.04[(a)]		
Effect of APA on WA			0.92	1.9		
Membership allocations						
Intercept δ1					0.86	2.36

implies a high possibility of data separation in Class 2. Following the approach in (Atasoy et al., 2013), we excluded WA from the choice set of individuals in Class 2 and re-ran the model. All the high standard errors disappeared. Thus, we decided to report the estimates of the LCC model with WA being excluded from the choice set of individuals in Class 2.

	Base model		ICLV model		LCC model	
	Estimate	t-test	Estimate	t-test	Estimate	t-test
EN					-0.35	-1.85
APA					0.40	2.03
Model statistics						
Number of estimated parameters:	21		73		75	
Number of respondents	821		821		821	
Number of observations	1840		1840		1840	
Number of draws	10,000		10,000		10,000	
Final log likelihood	-916.0798		-14194.9		-14193.45	
Rho-squared (ρ)	0.530		0.319		0.319	
Akaike Information Criterion (AIC)	1874.16		28535.8		28536.91	
Bayesian Information Criterion (BIC)	1973.081		28879.67		28890.2	

*Note: **(a)**: <u>Not</u> significant at 90% level of confidence; **DA**: Driver Alone; **RAIL**: Subway/Train; **BI**: Bicycle; **WA**: Walking; **Accident_yes_**: having involved in an accident in the past; **Elder_**: aged from 65 and above; **High_edu_**: having more than 7 education years after junior high school; **Male_**: being a male; **Part-time_job_**: only have a part-time job; **Company_staff_**: a full-time company worker; **High_income:** having annual income of more than 750,0000 JPY (~ 69,000 US Dollar); **Unemployed_**: without an occupation; Travel time and cost are measured in minute and Japanese Yen (JPY).*

First, all the estimates for mode attributes were found to be significant and in expected signs. This is in line with previous studies on mode choice, i.e. travel time and travel cost should negatively influence mode utilities. Interestingly, only out-vehicle travel time was found to influence rail utility. This, combined with the significant effect of transfer times, implies that rail travelers may be more concerned about waiting time than in-vehicle travel time. The significant positive effect of travel distance on car utility in the Base model and ICLV model supports this finding as trips with longer distance may result in more out-vehicle time if train is used (e.g., due to more transfers), and hence motivating the travelers to choose car. As expected, respondents were found to be more sensitive to the travel time of non-motorized modes than motorized-modes. For example, the estimates of the parameters of travel time by BI and WA have (slightly) higher absolute values than travel time by DA. This difference in the time sensibility is, however, much higher when the respondents are grouped into different classes. In Class 1 for example, the coefficients for travel time by BI and WA are nearly five times higher than travel time by DA.

Next, some personal characteristics were found to be significant determinants of mode utilities. Being involved in an accident is likely to discourage travelers from choosing non-car modes. While more educated people tend to prefer railway, we found men to be more likely to prefer cycle than women. For occupation characteristics, the result implies that respondents with part-time job saw railway as more preferred than the others.

Finally, we found significant and expected effects of environmentalism and APA on mode choice, nevertheless in different ways. In the results from the ICLV model where environmentalism was allowed to directly affect RAIL utility, and APA was modeled to cause BI and WA utility, only the effect of APA on WA utility was found as significant. Thus, it is equivalent to state that an increase in APA is expected to lead to an increase in the utility for WA whereas no similar effect was found for the case of environmentalism. However, the estimates from the LCC model reveal evidence in support of the effects of environmentalism and APA on mode choice. Specifically, we found significant negative effect of environmentalism and significant positive effect of APA on the probabilities of being in Class 1 and Class 2, respectively. From the definition of Class 1 and Class 2 in Equation 6, an increase in environmentalism is assumed to lead to higher probability of falling into Class 2 while an increase in APA will lead to higher probability of being in Class 1. Following this result, Class 2 can be named as *pro-environmental group* and Class 1 be named as *pro-physical activity group*. Figure 2 shows the Predicted Mode Shares (PMS) of the two classes[24]. While the PMS of DA in the two classes are not noticeably different (e.g., the PMS of DA in Class 1 is about 8% higher than that in Class 2), the main distinction between the two classes lies in the great differences in the distributions of PMS of the remaining alternatives. The PMS of RAIL in Class 2 is more than three times higher than in Class 1. In contrast, only 0.97% of individuals in Class 2 were predicted to choose BI (while that in Class 1 is 6.15%). Those individuals were predicted to even not choose WA in their frequent trips, and hence, WA was excluded from their choice sets. These results imply that respondents who have greater cares for environmental problems are more likely to belong to Class 2, the class of respondents who have showed more choices for RAIL than the others. In contrast, respondents with greater cares for physical activity are more likely to belong to Class 1, the class of respondents who have showed a mode share pattern more skewed towards BI and WA than the remaining respondents. Thus, in this way, environmentalism was found to be associated with more choices for RAIL, and APA was found to be associated with more choices for BI and WA.

[24] To calculate the predicted mode shares of two classes, we first divided our whole sample into three *sub-samples* corresponding to the three trips reported. Each sub-sample was then further divided into 11 *homogenous sub-samples* corresponding to the 11 choice sets generated from the 4 considered alternatives of DA, RAIL, WA and BI. In total, we have segmented our 1840 observations into 33 *homogenous sub-samples* so that all the respondents in the same *homogenous sub-sample* have the same choice set. We then calculated the individual predicted mode shares of 33 *homogenous sub-samples* by using the same estimates of the LCC model shown in Table 5. Finally, the predicted mode shares for each class were calculated by aggregating these individual mode shares. By this segmentation, the predicted mode shares did not account for the correlations between repeated choices.

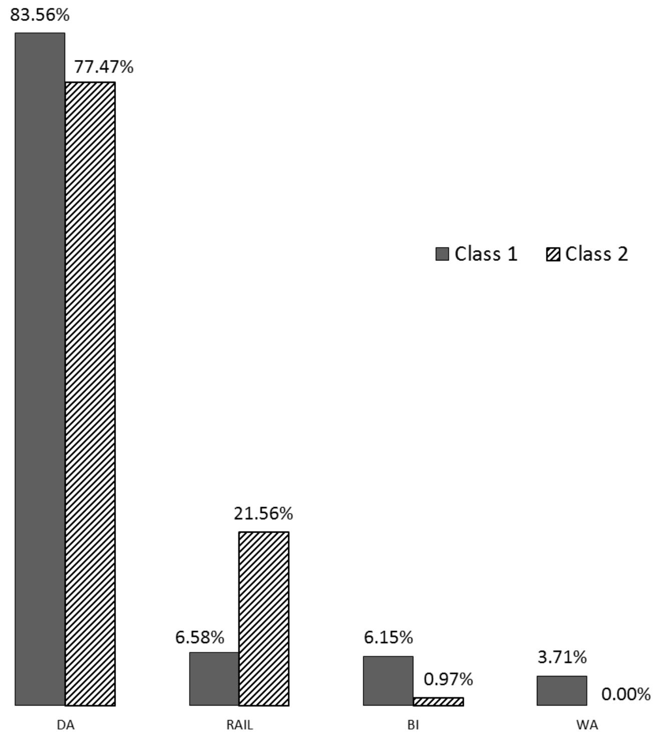

Figure 12. The predicted mode shares for two classes in the LCC model in examining the effects of environmentalism and APA on mode choice behaviors.

To confirm the findings from the LCC model, a validation analysis was conducted to evaluate the performance of the LCC model, and then followed by a sensitivity analysis for observing the sensitivities of mode shares by all modes (DA, RAIL, BI and WA) to the changes in the values of environmentalism and APA. The result of the validation analysis is shown in Appendix B, with acceptable predictability of the LCC model being found. The sensitivity analysis followed the "One-at-a-time" approach (e.g., when the sensitivities of mode shares to environmentalism are examined, the values of APA are fixed, and vice versa). In all cases, the possible values for environmentalism and APA are allowed to vary between (1; 2; 3; 4; 5) as similar to the possible values of their indicators. The sensitivity analysis was based on Eq. 21, Eq. 23, and Eq. 24 with the parameters fixed to the corresponding values in Table 5 and the mode shares in each class are fixed to the values shown in Figure 12. The result of the sensitivity analysis is shown in Table 6 and Table 7.

Table 6. The result of the sensitivity analysis for environmentalism (EN) in examining the effects of environmentalism and APA on mode choice behaviors.

Mode share predicted / Value of environmentalism	DA	RAIL	BI	WA
1	82.63%	8.82%	5.41%	3.14%
2	82.33%	9.56%	5.16%	2.95%
3	81.95%	10.47%	4.86%	2.72%
4	81.50%	11.55%	4.51%	2.44%
5	81.01%	12.74%	4.11%	2.14%
Percentage increase from EN = 1 to EN = 5	-1.97%	**44.52%**	-24.05%	-31.84%

Table 7. The result of the sensitivity analysis for APA in examining the effects of environmentalism and APA on mode choice behaviors.

Mode share predicted / Value of APA	DA	RAIL	BI	WA
1	80.86%	13.09%	3.99%	2.05%
2	81.44%	11.71%	4.45%	2.40%
3	81.95%	10.47%	4.86%	2.72%
4	82.37%	9.45%	5.20%	2.98%
5	82.71%	8.64%	5.47%	3.19%
Percentage increase from APA = 1 to APA = 5	2.28%	-34.03%	**36.99%**	**55.32%**

The results of the sensitivity analysis are in line with the results in LCC model. For example, when environmentalism increased from 1 to 5, the predicted mode share for DA increased unnoticeably but the remaining mode shares changed significantly. The mode share predicted for RAIL increased from 8.82% to 12.74% with the percentage increase of 44.52%. The same fact can be observed for the case of APA with the significant increases in the predicted mode shares for BI and WA when APA increased. This results thus provide more supportive evidences for the effects of environmentalism and APA on mode choice.

4.5. Discussions

Overall, the expected effects of environmentalism and APA on mode choice behaviors were confirmed in this case study. Several important findings can be derived from the estimation results.

First, environmentalism was found to be associated with an increase in the mode share of RAIL in the LCC model through its effect on the class membership assignments. In all studies in our review, environmentalism was treated by directly incorporated into the utility functions and the outcomes are not always expected, for example when no significant effects were found or the effects were not as expected (Politis et al., 2012; Sottile et al., 2015b). Several explanations of these unexpected cases focus on the cognitive dissonance phenomenon, that concerns for such global issues can only be translated into behavioral outcomes when the behaviors are easy to perform whereas travel behaviors are not among them. We agree that it might not sound realistic to expect a strong relation between a general attitude and a specific behavior, such as in this case between environmentalism and mode choice. However, we also suggest that due to this loose association, analyzing techniques should focus more on heterogeneities within the analytic samples in order to test the theory with more homogenous samples. In the latent class framework, we found significant effect of environmentalism in assigning individuals into Class 2, and this class showed mode share for RAIL be three times higher than that of the remaining class. In this sense, our conclusion that individuals with stronger environmentalism showed more choices for RAIL, a form of mass transport and environmentally friendly travel behaviors, can serve as an alternative way of illustrating the effect of environmentalism on mode choice.

Second, as the positive effect of APA on mode choice have been verified in both ICLV model and LCC model, this factor should be included in the list of determinants of mode choice. Specifically, we found positive effects of APA on the utilities and mode shares of bicycle and walking. This particularly benefits the practices in public policies. Raising people awareness of the importance of physical activity for health may result in the improvement in the overall level of physical activity in the intervened population and at the same time, encourage them to use more physically active transport modes. This positive outcome should be recognized and welcomed by both health and transport sectors and if such scenario happens, promotion campaigns of improving APA may have more supporters to be implemented. When people perform more physically active behaviors and use more physically active transport modes, both benefits for personal physical health and environmental benefits in terms of energy saving can be expected.

Finally, it might be interesting to compare the estimates of environmentalism and APA when being investigated by using the same dataset. In the estimates of the ICLV model where data of a pooled sample is used, only APA showed a significant effect on walking. Thus for a mode choice situation when heterogeneities in terms of taste variations in the sample are ignored, the interests in personal benefits, such as physical health benefit, are stronger than cares for social benefits, such as the protection for the ecology system. In other words, at least for this context of mode choice behaviors, respondents in our analytic sample show higher priority for their private benefit than social benefits. This behaviorally sounding fact might be beneficial for evaluating the feasibilities of social intervention campaigns when a number of behavior domains are on the table.

4.6. Conclusions

In this case study, we employed an ICLV model framework and a LCC model framework for examining the effects of environmentalism and APA on mode choice, followed by additional sensitivity and validation analyses. Using data collected in Nagoya, Japan, we found an association between environmentalism and the increased share of rail in Class 2, the pro-environmental group, from Class 1. The latent class framework was useful in unraveling the effect of environmentalism on mode choice that is frequently reported as insignificant in previous studies. For APA, we found both significant coefficients in the utility functions of bicycle and walking and in the membership function of the LCC model. This study thus confirmed that environmentalism has an indirect effect on the choices of rail, a form of mass transit, and APA, on the other hand, exhibited significant effects on both mode utility and mode choice of bicycle and walking. In addition, we found higher cares for physical activity, a form of private benefits, than cares for environmental issues, a kind of social benefits, in the analytic sample. This case study thus suggested that environmentalism and APA should be appended to the list of travel behavior determinants, and that transport and health policies can be coordinated though the factor APA. We also suggest future study to employ the framework of the LCC model in exploring the effects of latent variables on mode choice models.

Chapter 5: Examining the effect of APA on mode choice behaviors with parameter bias correction

5.1. Introduction

This chapter followed Chapter 4 in examining the effect of APA on mode choice behaviors. In the current case study, we examined the effect of APA on mode choice behaviors under highly unbalanced mode share patterns and in a binary choice model context. In rural areas in developed countries, car use often dominates other mode uses, such as public transport uses. High dominances of car use over other mode uses cause mode share patterns to be skewed greatly toward the dominant mode. Discussed in Section 3.1.5, data separation can occur in these situations which will result in bias in the parameter estimates. In other word, we postulate that the effects of APA on mode choice are prone to be biased in the presence of data separation. Inspired by this fact, we attempted to examine the effect of APA on mode choice under a highly unbalanced mode share pattern. The result of this study first serves as a confirmation of the effect of APA on mode choice found in Chapter 4. In addition, we expected that this context of a highly unbalanced mode share pattern, that demands a correction solution for data separation phenomenon, will ultimately lead to some methodological values not only for studies of the topics close to this dissertation but also for general mode choice studies.

The examination on the effect of APA on mode choice was conducted using data of respondents living in Asuke, a rural area in Japan. This rural context appeared to fit well with our objectives in this study. There exists a disparity between rural and urban areas in both level of physical activity and opportunities for physical activity. For instance, compared with urban residents, those living in rural areas exhibit lower levels of physical activity (Cleland et al., 2017; Ozemek et al., 2019) and higher obesity prevalence (Befort et al., 2012). Rural areas are also considered as physical activity disadvantaged and the need to promote physical activity among rural adults is urgent (Mitchell et al., 2019). In addition, residents in rural areas are highly dependent on car use (Gray et al., 2001; Marr, 2015; Wiersma et al., 2015) and more time spent in the car is associated with an increase in obesity (Wener and Evans, 2007). Thus, an effect of APA on mode choice, if proven, can contribute to the realizations of policies aiming at promoting physical activities in rural areas. Such implementations would ultimately contribute to efforts in reducing the inequality in physical activity accessibility between rural and urban areas. In this sense, the issue of physical inactivity is more urgent in rural areas than in urban areas. The findings related to APA of this dissertation thus will be more meaningful if it is contextualized in a rural area.

In this study, we employed the (standard) ICLV model framework in exploring the effect of APA. We postulated that APA has an effect on bus utility and, hence, affecting the choices between bus and car. This assumption is based on the fact that bus travelers have to spend certain time in cycling or walking to/from bus stations. In addition, the rural context of this study led to a highly unbalanced mode share pattern. We thus checked for data separation in the input data and then applied a solution for this issue.

5.2. Methodological framework

In this case study, the effect of APA on bus utility was modeled through the framework of the standard ICLV model, i.e. ICLV model with a sequential estimation method and indicators considered continuous variables. Thus, the latent variables are treated as similar to other exploratory variables. In addition, we consider explicitly the relation between general attitude and behavior-specific attitudes within the context of a mode choice model (See 2.3 for more detail). The effect of APA on bus utility was mediated by the specific attitude toward bus use. Moreover, we also include attitude toward car use in our model to observe how this attitude affects car utility. Therefore, there are three latent variables in our ICLV models:

- Attitude toward physical activity (APA)
- Attitude toward bus use (Att_B)
- Attitude toward car use (Att_C)

Our general model framework, as shown in Figure 13, consists of a structural model and a choice model, as described in Section 3.1.3. We applied this model framework for two data sets of clinic/hospital trips and shopping trips.

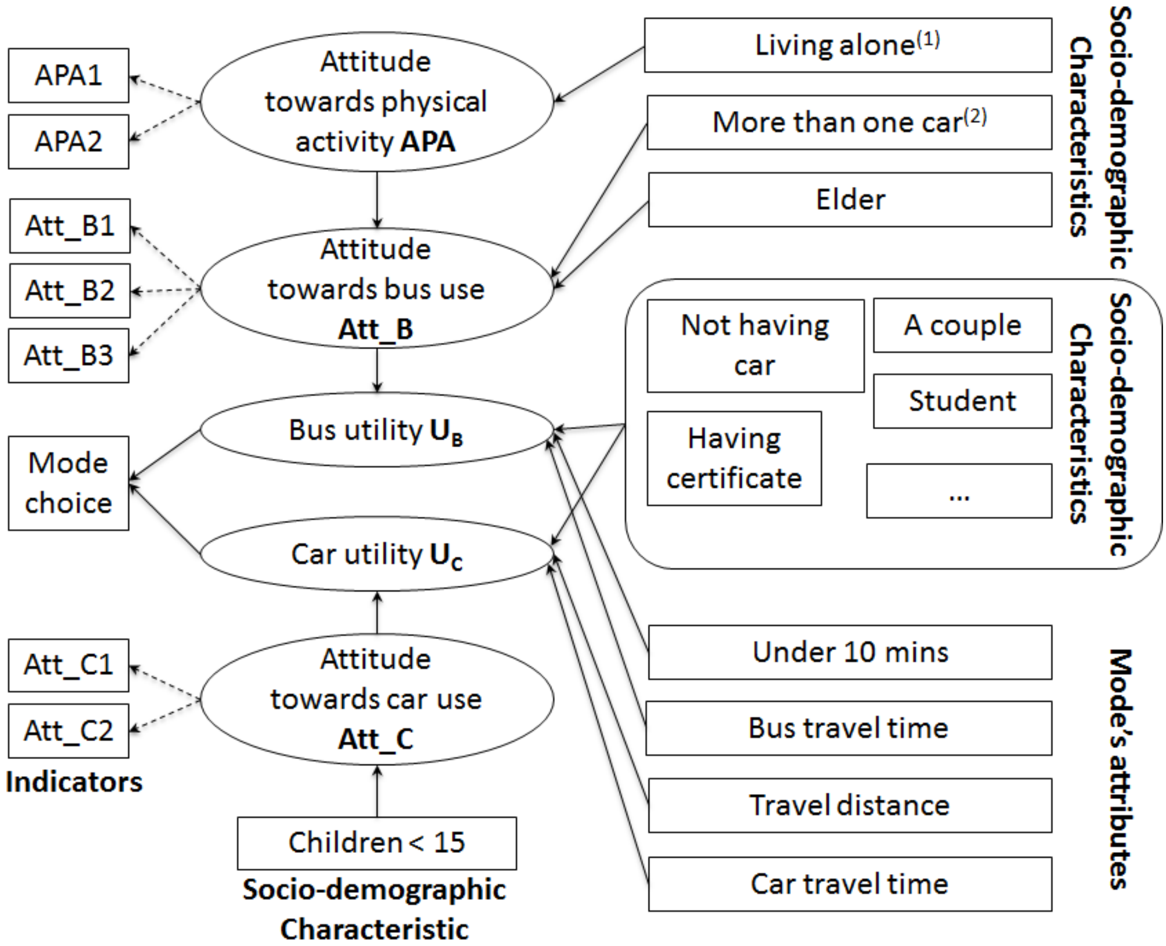

Figure 13. The model framework for examining the effect of APA on bus utility.

Note: The variables (1) and (2) are included in the clinic/hospital trips and shopping trips models, respectively. The "…" symbol means, for brevity, there are other variables not shown in this diagram. The solid arrows represent the structural relations while the dashed arrows show the measurement relations. The latent variables and observable variables are depicted as ovals and rectangles, respectively, as commonly used notations in choice models (Ben-Akiva and Bierlaire, 1999; Morikawa et al., 2002) and structural equation models (Bollen, 1989). See the note under Table 15 for the explanations for the names of variables.

To find the relevant determinants of the three attitudes, we follow the approach in Vredin Johansson et al. (2006); we first test all the socio-demographic variables in the estimation of the SEM model, and we then retain only the significant predictors (at 5% significance) in the later steps. The results from running separate SEMs for clinic/hospital trips and shopping trips suggest that only some socio-demographic variables should be retained, as shown in Figure 13. The measurement models for attitudes were developed by first using a PCA and VARIMAX rotation with the results shown in Table 8. Then, a CFA was conducted to check the goodness-of-fit of the measurement models, and to ensure significant factor loadings. To conduct CFA, the indicators should be checked for normality first as the MLE for CFA and

SEMs is based on this assumption. Mardia's test (Mardia, 1970) for the multinormality of the indicators was performed using a multivariate normality tests (MVN) package (Korkmaz et al., 2014), and the results showed the skewness and kurtosis in the model for clinic/hospital trips as 2582.3 and 56.4, respectively, and in the model for shopping trips as 3568.9 and 71, respectively. Clearly, the input data for both models were statistically non-normal in terms of excessive skewness and/or kurtosis; therefore, we applied a bootstrapping technique to account for these violations (Finney and DiStefano, 2013). The CFA test was conducted using R (R Core Team, 2018) and the Lavaan package (Yves, 2012); the results are shown in Table 9 with acceptable goodness-of-fit and significant factor loadings ranging from 0.63 to 0.91 (standardized).

Table 8. The summary of the PCA results in examining the effect of APA on bus utility

Factor	Indicator	Factor loading in EFA		Cronbach's alpha	
		Clinic/ hospital	Shopping	Clinic/ hospital	Shopping
APA	APA1: Walking is good for your health	0.80	0.79	0.61	0.75
	APA2: Going out is useful for maintaining your health	0.84	0.84		
Att_B	Att_B1: I love to use the bus	0.78	0.76	0.77	0.61
	Att_B2: I'm planning to use the bus more	0.87	0.88		
	Att_B3: Life becomes inconvenient if the bus stops running	0.81	0.79		
Att_C	Att_C1: The car is convenient	0.86	0.84	0.76	0.76
	Att_C2: The car is an indispensable tool	0.89	0.91		

Table 9. The summary of CFA results in examining the effect of APA on bus utility

Factor	Indicator	Factor loading in CFA		Goodness-of-fit of CFA model		
		Clinic/ hospital	Shopping	Criteria	Clinic/hospital	Shopping
APA	APA1	0.65**	0.63**	Chi-square	31.48	45.38
	APA2	0.89**	0.88**	df	11	11
Att_B	Att_B1	0.67**	0.63**	Chi-square/df	2.86	4.13
	Att_B2	0.69**	0.69**	RMSEA	0.06	0.07
	Att_B3	0.64**	0.63**	GFI	0.99	0.98
Att_C	Att_C1	0.82**	0.91**	NFI	0.97	0.97
	Att_C2	0.74**	0.68**	CFI	0.98	0.97

*Note: **p < 0.01; the standard errors (and the corresponding p-values) are calculated using unstandardized scores of observed variables (Bollen, 1989). See Section 3.2.2 for the explanations for abbreviations of goodness-of-fit criteria.*

The structural models were estimated by using R (R Core Team, 2018) and the Lavaan package (Yves, 2012). A special function of the Lavaan package enables the estimation of fitted values for latent variables after the main model has been fitted. These fitted values are used in the choice model later as fixed continuous values.

We checked the possibility of data separation in the data set as the shares of the bus choice in both the clinic/hospital and shopping trip models are very low (5.08% and 3.27%, respectively). As it turned out, the existence of data separation was clear in the input data: (1) Table 10 shows the two-way contingency table with several zero or near zero cells (in shade) and; (2) The brglm2 package (Kosmidis, 2017) in R showed that the data were observed statistically as separated in both cases of clinic/hospital trips and shopping trips and; (3) The package PythonBiogeme (Bierlaire, 2018) reported convergence error and; (4) The above signs of data separation disappeared with the removal of the variables associated with zero cells in Table 10 (e.g., the occupational variables). Firth method was then embedded into the estimation process of the two ICLV models by using the Logistf package (Heinze and Ploner, 2004).

Table 10. The two-way contingency for bus choice and socio-demographic categorical variables in examining the effect of APA on bus utility

Dummy variable (X) / Bus choice (Y)	Living alone	A couple	With children	Three generations	Other family types	Children < 15	Not having car	Having one car	More than one car	Male	Elder
Clinic/hospital trips											
Y = 0; X = 0	539	413	338	443	511	451	548	454	120	287	237
Y = 0; X = 1	22	148	223	118	50	110	13	107	441	274	324
Y = 1; X = 0	22	27	22	24	25	26	21	21	18	26	2
Y = 1; X = 1	8	3	8	6	5	4	9	9	12	4	28
Shopping trips											
Y = 0; X = 0	675	522	425	570	648	576	701	573	146	384	341
Y = 0; X = 1	35	188	285	140	62	134	9	137	564	326	369
Y = 1; X = 0	17	22	19	18	20	22	15	17	16	22	0
Y = 1; X = 1	7	2	5	6	4	2	9	7	8	2	24
Dummy variable (X) / Bus choice (Y)	Having certificate	Under 10 mins	Company worker	Public servant	Student	Part-time worker	Housework	Agriculture work	Unemployed	Other occupations	
Clinic/hospital trips											
Y = 0; X = 0	522	50	471	529	546	473	491	496	391	528	
Y = 0; X = 1	39	511	90	32	15	88	70	65	170	33	
Y = 1; X = 0	23	4	30	30	30	30	27	29	4	30	
Y = 1; X = 1	7	26	0	0	0	0	3	1	26	0	
Shopping trips											
Y = 0; X = 0	687	72	581	663	705	588	603	645	520	661	

Dummy variable (X) / Bus choice (Y)	Living alone	A couple	With children	Three generations	Other family types	Children < 15	Not having car	Having one car	More than one car	Male	Elder
Y = 0; X = 1	23	638	129	47	5	122	107	65	190	49	
Y = 1; X = 0	16	1	24	24	24	24	22	21	4	24	
Y = 1; X = 1	8	23	0	0	0	0	2	3	20	0	

Note: Both bus choice and exploratory categorical variables are dummy coded as 0 or 1, corresponding to being unobserved or observed; the numbers in the table are the numbers of the observations corresponding to four pairs of the possible values of bus choice and other variables. See the note under Table 15 *for the explanations for the names of variables.*

5.3. Data set

Our data set is extracted from the first wave of a mobility management program conducted in Asuke, Toyota City, Japan. Asuke is a small rural town with about 8,000 inhabitants. Similar to other rural areas in Japan, people in Asuke are generally dependent on car use for various daily activities. There are two types of buses currently available in Asuke as well, the community bus (or "aimaru basu" in Japanese) and the school bus. The community bus system in Asuke is currently running with 13 fixed routes. Each route is served by bus in a specific weekday (e.g., every Thursday) and in that day, one bus will run one time in the morning (in one direction) and one time in the afternoon (in the opposite direction). To support the community bus system in Asuke, school buses have been utilized as well to serve people of all ages, although their main riders are students. The school bus system with 11 fixed routes only operates on times when students go to/from schools (e.g., twice a day in every weekday except in case of school vacations and events).

As part of the mobility management program in Asuke, a mail-based survey was conducted in September 2017. Of the 2,838 household members invited to respond to the survey, 1,009 households replied in October 2017 (35.6% response rate). After processing the raw data, we had answer sheets corresponding to 2,352 respondents. In each household, one person was asked to provide general information for all the members in his/her family, such as the number of cars, the house composition, and the distance to the nearest bus station. All the household members were asked to: (1) give general information, such as age and sex; (2) select their usual transport modes from a list; (3) report their chosen mode and the corresponding level of service (LOS) (e.g., travel time and cost) for four frequent trips (work trips, clinic/hospital trips, shopping trips, and outing trips); and (4) rate their opinions on a five-point Likert scale of the questions regarding pre-designed psychological factors.

To ensure that the respondents in our analytic sample truly had a choice between bus and car[25], we applied the following screening criteria:

Criterion (1): All the required fields of the questionnaire related to our model were filled by the respondent;

Criterion (2): Either the community bus or the school bus was available for the reported trip[26] and the chosen mode was either car or bus.

A respondent eligible to be included in our analytic sample was someone who satisfied the above two criteria. After screening, the number of respondents is summarized in Table 11.

Table 11. The summary of the number of respondents in the screening step in examining the effect of APA on bus utility

	The number of respondents			
	Work trips	clinic/hospital trips	Shopping trips	Outing trips
- Satisfies Criteria (1)	852	1555	1536	1398
- Satisfies Criteria (1) + (2)	557	591	734	125

As Table 11 shows, the number of the respondents eligible for the analysis (who truly had a choice between bus and car) was reduced significantly after the screening. Our summary in Table 11 indicates that the bus option was not possible for many trips. This may be a partial explanation why people remain highly dependent on car use in rural areas in Japan.

The mode shares based on the eligible respondents are shown in Figure 14. As the number of bus choices observed for work trips was critically low, and the choice model for the outing trips yielded no significant estimates, we narrowed our study to mode choice models for the

[25] In fact, the list that the respondents could select their chosen modes included "Motorbike", "Walking", "Cycling", and "Others" in addition to the main options of "Car" and "Bus". However, the observed mode share pattern was highly skewed towards the car alternative, and this caused some problems in the model estimation process (see the previous sub-section for more details). We proposed a bias correction method to deal with this issue. Unfortunately, the software that enabled us to apply this method could only work with binary choice models. We thus decided to retain "Car" and "Bus" in the analytic choice set as reducing car use and increasing bus use can benefit both health policies (e.g., improved levels of physical activity) and transport policies (e.g., reduced environmental impacts). This, however, may not be true for the remaining modes. For example, although walking and cycling are generally encouraged by health policies due to health benefit outcomes, they are only available for short trips which might not be the target of transport policies.

[26] Bus is considered available for a given trip if: (1) The distance from the traveler's home to its nearest bus stop and from the traveler's destination to its nearest bus stop are both lower than 1 km *and;* (2) There exists at least one (school/community) bus route that connects these two bus stops.

clinic/hospital trips[27] and shopping trips. In these two trip types, clearly, the mode shares are highly unbalanced.

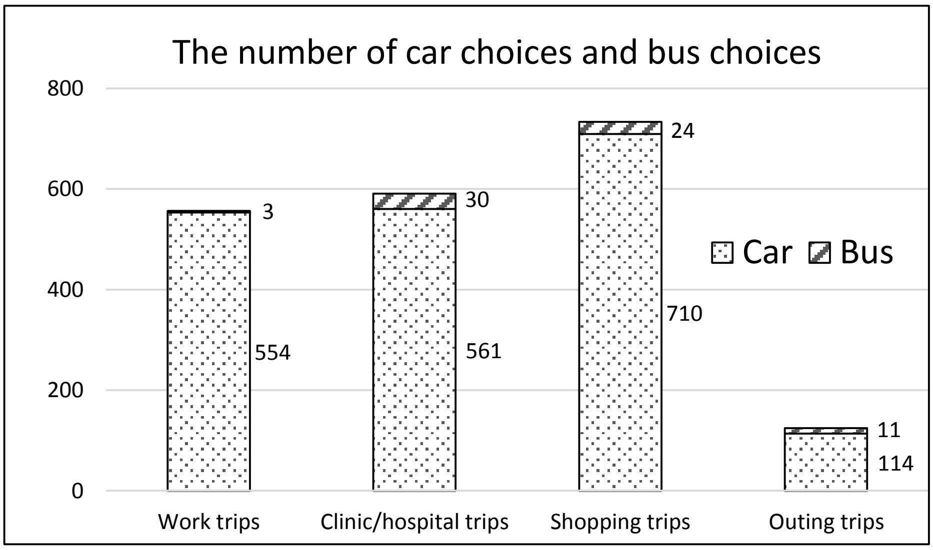

Figure 14. The distribution of bus and car choices in the eligible sample

Note that because the respondents did not report the LOS for their unchosen modes, and in favor of using input data from the same source, we decided to use the estimated values (e.g., based on the bus timetables and on Google Maps suggestions) for both the LOS of chosen and unchosen modes of the respondents. In this study, we consider three LOS variables: (door-to-door) travel time by car, (in-vehicle) travel time by bus, and travel distance.

Table 12. The statistics on the eligible sample in examining the effect of APA on bus utility

Socio-demographic characteristic	Clinic/hospital trip model	Shopping trip model	Socio-demographic characteristic	Clinic/hospital trip model	Shopping trip model
Family type (%):			Age (%):		
- Living alone	5.08	5.72	- Under 19	1.86	0.27
- A couple	25.55	25.89	- From 19-44	11.51	10.49
- Parents with children	39.09	39.51	- From 45-64	25.21	35.42
- Three generations	20.98	19.89	- 65 and older (elder)	61.42	53.81
- Others	9.31	8.99	Occupations (%):		
Having children under 15 years old (%):			- Full-time company worker	15.23	17.57
- Yes	19.29	18.53	- Full-time public servant	5.41	6.40
- No	80.71	81.47	- Student	2.54	0.68
Car ownership (%):			- Part-time worker	14.89	16.62

[27] As serious illnesses generally happen infrequently, we assumed that people's frequent trips to clinic/hospital are mainly for minor illnesses or health maintenance reasons. In these case, bus use is still available.

Socio-demographic characteristic	Clinic/hospital trip model	Shopping trip model	Socio-demographic characteristic	Clinic/hospital trip model	Shopping trip model
- Not having cars	3.72	2.45	- Housework	12.35	14.85
- Having one car	19.63	19.62	- Agriculture	11.17	9.26
- More than one car	76.65	77.93	- Unemployed	33.16	28.61
Sex (%):			- Other	5.25	5.99
- Male	47.04	44.69	Trip attribute: mean (standard deviation)		
- Female	52.96	55.31	- Car travel time (minutes)	11.68 (6.88)	11.62 (7.54)
Having a long-term care need certificate[1] (%):			- (In-vehicle) Bus travel time (minutes)	14.69 (8.92)	14.49 (9.12)
- Yes	7.78	4.22			
- No	92.22	95.78	- Travel distance (km)	5.97 (3.48)	6.00 (3.82)

Note: (1) "Long-term care need" is a Japanese governmental program that the insured people can receive long-term cares, such as health, medicine, and welfare, when they become old.

Table 12 summarizes the basic socio-demographic characteristics and trip attributes of the respondents used in the two models for clinic/hospital trips and shopping trips. The households of parents with children dominated the sample, and about 20% of the households had children under age 15. The car ownership patterns in the sample reflect the car dependence in this area, as more than 96% of the households had at least one car. While the sex statistic was generally balanced, the age distribution in the sample represents the typical aging problem in Japan, as more than half of the respondents were over age 65. A small portion of the respondents used long-term care insurance services, such as bathing, nursing care, and rehabilitation, and unemployed was the most common occupation response. Finally, the average travel time by car and the average (in-vehicle) travel time by bus do not differ noticeably in both two trip purposes.

The last part of the questionnaire was designed to capture the respondent's psychological factors. In addition to APA, we measured the respondent's attitudes towards each mode.

5.4. Estimation result

The results from the ICLV models and base models (where latent variables and their indicators are removed) are summarized in Table 13 and Table 14. In addition, the ICLV models had better explanation powers for the observed mode choices compared to the base models thanks to the added information of the two specific attitudes.

Table 13. The estimates of the structural models in examining the effect of APA on bus utility

			Clinic/hospital	Shopping
Structural relation				
Living alone	→	APA	0.26(**)	N/A
APA	→	Att_B	0.67(**)	0.62(**)
Elder	→	Att_B	0.29(**)	0.22(**)
More than one car	→	Att_B	N/A	-0.18(**)
Children < 15	→	Att_C	0.13(**)	0.13(**)
Measurement relation				
APA	→	APA1	1(constrained)	1(constrained)
APA	→	APA2	1.54(**)	1.62(**)
Att_B	→	Att_B1	1(constrained)	1(constrained)
Att_B	→	Att_B2	1.47(**)	1.5(**)
Att_B	→	Att_B3	1.26(**)	1.22(**)
Att_C	→	Att_C1	1(constrained)	1(constrained)
Att_C	→	Att_C2	1.35(*)	0.86(**)
Fit measure				
Chi-square			170.45	201.23
df			42	30
Chi-square/df			4.06	6.71
RMSEA			0.07	0.09
GFI			0.93	0.93
NFI			0.86	0.85
CFI			0.89	0.87

*Note: **p < 0.01; *p < 0.05; N/A: this parameter is not available by the model specification. See the note under Table* 15 *for the explanations for the names of variables.*

Table 14. The estimates of choice models (values when run without bias correction in parentheses) in examining the effect of APA on bus utility

	Clinic/hospital		Shopping	
	Base model	ICLV model	Base model	ICLV model
Estimates				
Intercept	-1.97(-3.1)	-1.69(-2.72)	**-4.68**(-26.48)**	-5.46(-27.8)
Living alone	-0.53(-0.57)	-0.86(-1.02)	-1.12(-1.3)	-1.64(-1.98)
A couple	**-1.82*(-2.03*)**	**-2.15*(-2.52*)**	-1.63(-1.94)	**-2.25*(-2.92*)**
With children	-0.35(-0.36)	-0.45(-0.51)	-0.19(-0.08)	-0.59(-0.65)
Three generations	0.2(0.31)	0.05(0.13)	1.49(2.02)	0.99(1.53)
Children < 15	0.33(0.32)	0.61(0.62)	-0.1(-0.37)	-0.23(-0.45)
Not having car	1.27(1.41)	**1.65*(1.93*)**	**2.13**(2.56**)**	**2.66**(3.42**)**
More than one car	**-1.38*(-1.55*)**	**-1.51*(-1.74*)**	**-1.97**(-2.33**)**	**-1.83*(-2.44*)**
Male	-0.91(-1.07)	-0.7(-0.87)	**-1.63*(-2.07*)**	-1.38(-1.86)
Elder	0.47(0.69)	-0.3(-0.2)	1.64(20.54)	0.84(19.21)
Having certificate	0.05(0.02)	0.05(0.02)	**1.31*(1.51*)**	**1.56*(2.01*)**
Under 10 mins	-0.93(-1.01)	-1.01(-1.11)	0.23(0.62)	-1.22(-1.37)
Company worker	-0.65(-20.47)	-0.95(-20.83)	0.39(-16.51)	3.08(-11.2)
Public servant	0.13(-20.72)	-0.61(-21.57)	1.44(-16.16)	3.86(-9.19)
Student	0.06(-21.53)	-0.18(-21.72)	2.75(0.43)	4.79(3.46)
Part-time worker	-1.5(-21.51)	-1.7(-21.83)	-0.41(-18.52)	2.46(-14.66)
Housework	0.46(1.19)	0.32(0.92)	0.01(1.93)	2.46(5.55)
Agriculture work	0.51(0.98)	0.61(0.97)	1.48(3.65)	4.4(8.04)
Unemployed	1.32(2.21)	1.09(1.83)	1.13(3.37)	3.46(6.9)

	Clinic/hospital		Shopping	
	Base model	ICLV model	Base model	ICLV model
Car travel time (minute)	0.02(0.03)	0.04(0.05)	-0.01(0)	0.04(0.05)
Bus (in-vehicle) travel time (minute)	-0.07(-0.08)	-0.08(-0.09)	0.02(0.03)	0(0)
Travel distance (km)	**-0.29*(-0.33*)**	**-0.28*(-0.34*)**	-0.04(-0.04)	-0.1(-0.12)
Attitude towards bus use		**1.88**(2.25**)**		**2.41**(3.28**)**
Attitude towards car use		**1.22*(1.38*)**		0.2(0.14)
Statistics				
Number of samples N	591	591	734	734
Final penalized loglikelihood LL*	-60.23	-45.75	-40.93	-27.35
Number of parameters k	22	24	22	24
LRI	0.39	0.53	0.53	0.68

*Note: **p < 0.01; *p < 0.05; N/A: this parameter is not available by the model specification. The Likelihood ratio index LRI = 1 – LL*/LL(0)*, where the LL* is the final loglikelihood of the fitted model and LL(0)* is that of the model without coefficients (the baseline model) (Train, 2009). Note that the LL(0)* also contains shrinkage (Jeffreys' (1946) invariant prior) that depends on the structure of the main model; See the note under Table* 15 *for the explanations for the names of variables; Significant estimates (at 95% confidence) were highlighted.*

In Table 14, clearly, only a few exploratory variables have a significant effect on bus choice. In both models for the two trip purposes, respondents who were part of a couple, or had more than one car in the household, tended to use the bus less. However, they were more likely to use the bus for clinic/hospital trips when the travel distance was longer. In addition, respondents who had a care need certificate were more likely to choose the bus for their shopping trips. Interestingly, we found no significant effects for (in-vehicle) travel time by bus and car on bus choice, which are commonly observed in mode choice models.

As our main interest in this study, the effects of attitudes towards bus use were significant and in the right sign in both models. The estimates from the structural models as shown in Table 13 indicate that APA significantly and positively influences attitudes towards bus use. Together, these results imply that APA has a positive effect on bus utility and that an increase in APA could lead to the higher probability of choosing a bus versus a car. In addition, attitudes towards car use had a significant negative effect on bus utility in the ICLV model for clinic/hospital trips.

Finally, the influence of data separation on the estimates of the choice models can be identified by examining the estimates and the corresponding standard errors of the two ICLV models as shown in Table 15.

Table 15. The estimates and standard errors of ICLV models with and without Firth bias correction for the two trip purposes in examining the effect of APA on bus utility

Variable	ICLV model for clinic/hospital trips				ICLV model for shopping trips			
	Estimate		Standard error		Estimate		Standard error	
	With bias correction	Without bias correction	With bias correction	Without bias correction	With bias correction	Without bias correction	With bias correction	Without bias correction
Intercept	-1.69	-2.72	1.66	2.22	-5.46	**-27.80**	2.44	**18898.47**
Living alone	-0.86	-1.02	0.88	0.98	-1.64	-1.98	1.02	1.27
A couple	-2.15	-2.52	0.85	1.03	-2.25	-2.92	0.97	1.29
With children	-0.45	-0.51	0.68	0.81	-0.59	-0.65	0.83	1.08
Three generations	0.05	0.13	0.76	0.91	0.99	1.53	0.95	1.39
Children < 15	0.61	0.62	0.68	0.86	-0.23	-0.45	0.84	1.41
Not having car	1.65	1.93	0.79	0.90	2.66	3.42	0.90	1.18
More than one car	-1.51	-1.74	0.65	0.80	-1.83	-2.44	0.69	0.97
Male	-0.70	-0.87	0.55	0.70	-1.38	-1.86	0.64	0.98
Elder	-0.30	-0.20	0.74	0.97	0.84	**19.21**	1.14	**18898.47**
Having certificate	0.05	0.02	0.59	0.65	1.56	2.01	0.67	0.80
Under 10 mins	-1.01	-1.11	0.64	0.78	-1.22	-1.37	0.85	1.34
Company worker	-0.95	**-20.83**	1.83	**44086.11**	3.08	**-11.20**	2.55	**28718.16**
Public servant	-0.61	**-21.57**	1.83	**76515.81**	3.86	**-9.19**	2.60	**47869.99**
Student	-0.18	**-21.72**	1.99	**110361.60**	4.79	3.46	2.92	**195151.50**
Part-time worker	-1.70	**-21.83**	1.73	**45252.69**	2.46	**-14.66**	2.19	**30142.67**
Housework	0.32	0.92	1.31	1.87	2.46	**5.55**	2.17	**8.44**
Agriculture work	0.61	0.97	1.34	1.82	4.40	**8.04**	2.18	**8.59**
Unemployed	1.09	1.83	1.22	1.78	3.46	**6.90**	2.08	**8.45**
Car travel time (minute)	0.04	0.05	0.04	0.05	0.04	0.05	0.05	0.07
Bus (in-vehicle) travel time (minute)	-0.08	-0.09	0.05	0.06	0.00	0.00	0.06	0.08
Travel distance (km)	-0.28	-0.34	0.13	0.16	-0.10	-0.12	0.17	0.23
Att_B	1.88	2.25	0.43	0.54	2.41	3.28	0.55	0.85
Att_C	1.22	1.38	0.49	0.60	0.20	0.14	0.57	0.80

*Note: **With children**: having children in the family; **Three generations**: including three generations in the same family; **Children < 15**: Having children under 15 years old in the family; **Elder**: ≥ 65 years old; **Having certificate**: in possession of a long-term care need certificate; **Under 10 mins**: living under 10 minutes from the nearest bus station; Values of estimates and standard errors without bias correction that are excessively biased are shown **in bold**; All socio-demographic characteristic variables are dummy coded.*

The variables with estimates and standard errors excessively biased due to data separation are all categorical variables with zero or nearly zero cells in the contingency table in Table 10. This result is in line with the data separation detection in Section 5.2 where categorical variables with zero cells are considered as the cause of data separation. Additionally, the existence of some extremely high standard errors and estimates in models without Firth bias correction is a clear sign for the fact that maximum likelihood estimates do not exist in these models. When the bias correction method is applied by penalizing the likelihood function, the estimates are corrected by "pulling" towards zero (Firth, 1993). Accordingly, all the absolute values of the estimates shrink towards zero and the largest shrinkage applies to variables with zero or near zero cells in the contingency table. Another outcome of applying the bias correction method is the improvement in the stabilities of the estimates as no large standard errors were found. This implies the existence of maximum likelihood estimates in models with Firth method applied. Clearly, all the standard errors are reduced when penalized MLE is applied in place of the normal MLE and the maximum improvements are for variables of zero or nearly zero cells in the contingency table.

5.5. Discussions

The estimation results of two models with and without Firth bias correction method for clinic/hospital trips and shopping trips carry some interesting findings related to the objectives in this dissertation.

First, the results from this study confirmed the influence of attitudes on mode choice. In line with the literature in psychology, attitude toward bus use and attitude toward car use are still important determinants of bus and car utilities. Moreover, we found evidence that APA had an effect on bus utility. This result carries two main implications. First, the current list of influential factors for mode choice should be extended to include APA. In fact, the number of general attitudes explored in mode choice models is currently very limited even though general attitudes have some characteristics that are potentially more valuable for framing policies than specific attitudes. Second, transport policies can benefit potentially through increased bus ridership if people's awareness of the value of physical activity increases. These benefits can be translated into supportive arguments for the implementation of promotional campaigns from health policies that encourage more physical activity. In this sense, a link between transport and health policies might be a worthwhile consideration for policymakers.

Another finding is the usefulness of applying Firth bias correction method in binary mode choice models. In both cases with and without bias correction of two ICLV models, we found significant indirect effects of APA on bus utility (e.g., through the factor ATT_B). Thus, the effect of APA on mode choice behaviors was confirmed in a mode choice model under highly unbalanced mode share pattern. In addition, we found some other findings related to the Firth bias correction method which can contribute to methodological improvements for mode choice studies. For example, most of the variables with large biases in the parameters estimated and/or very high standard errors were categorical variables. According to Hosmer and Lemeshow (2013), this phenomenon can be explained by the fact that continuous variables have a greater overlap at their values than categorical variables. Thus, similar to logistic regression models, estimates of categorical variables in mode choice models are prone more to bias through data separation than continuous variables or variables with a larger overlap in their values. Thus, the attitude variables, which are commonly modeled as continuous variables in ICLV models, appear to be unaffected by the data separation phenomenon. This is illustrated in our study by the significant effects of two specific attitudes on bus utility in both ICLV models. Additionally, some estimates and standard errors of parameters of variables that have been specified as the cause of data separation are extremely high when the choice models are normally estimated (e.g., without any bias correction methods). However, the Firth method employed here by penalizing the likelihood function helped remove the first order of the bias and led to more stable estimates. It must be noted that the Firth bias reduction method also induces biases in the estimated probabilities and these biases should not be ignored if the events are rare (Puhr et al., 2017). Thus, in the case of extremely skewed mode share patterns, where the interest is in forecasting rather than in evaluating the effects of the explanatory variables, other methods for correcting the biases in the predicted probabilities can be applied. Overall, the Firth bias reduction method helped improve the performance of the choice models under the highly unbalanced mode share pattern by ensuring the existence of maximum likelihood estimates. For this reason, the choice sets considered in the choice models may be extended to include alternatives with very low shares, which, in normal cases, may be excluded by the analysts. In these cases, data separation should be checked and, if it exists, corrections should be made. Firth bias correction method then provides an alternative solution to the normal treatments for data separation (e.g., excluding out irrelevant variables from the model, which may cause model specification errors).

5.6. Conclusions

With the purpose to re-examine the effect of APA on mode choice in a highly unbalanced mode share context, this study employed the standard ICLV model framework and the Firth bias correction method for dealing with data separation. Data was collected in Asuke, a rural town in Japan where mode shares are highly skewed toward car choices. The result of estimating the structural model showed a significant regression coefficient of APA on ATT_B in both models for clinic/hospital trips and for shopping trips. Then in the result of the choice model, a significant coefficient representing for the effect of ATT_B on the bus utility was found. In addition, we found very large biases in the estimates and standard errors of the choice models. The Firth bias correction method significantly reduced these biases, leading to some improvements. Thus, this study confirmed that APA has an indirect effect on bus utility. This finding provides an additional support for the conclusion in Chapter 4, that APA should be viewed as a determinant of travel behaviors and transport and health policies should be coordinated through this factor. In addition, Firth bias correction method is an useful tool in dealing with issues caused by data separation in binary logit choice models. From this, we suggest that data separation should be checked whenever mode share pattern is highly skewed towards certain modes.

Chapter 6: The reciprocal relationships between environmentalism and car use behaviors

6.1. Introduction

In this chapter, we explored the potential effect of environmentalism on car use behaviors. Instead of conceptualizing mode uses as alternatives in a choice situation, this chapter views mode uses, such as car use, as being equal to the rate or frequency of the behavior in question. Car use behaviors are thus considered the rate of traveling by cars in a specific period.

Car use and car use reduction has become an important issue in transport studies. While playing an important role in providing mobility for various human activities, car use also induces a number of environmental problems (Gärling et al., 2002; Marshall and Banister, 2000; Steg, 2003a). It is estimated that the transportation sector accounted for approximately 14% of the total emitted global greenhouse gases in 2010 (Edenhofer et al., 2015), and 80% of all motorized road vehicles are used for private transportation (OECD, 1996). In addition to the consumption of scarce and limited materials, and energy for the production and operation of cars, solid wastes resulting from these processes also create disposal problems (Steg, 2003b). In urban areas, life quality is affected by car use in terms of noise, air pollution and traffic accidents (Steg, 2003a). Hence, reducing car use dependence has been specified as a goal of urban design leading toward viability and sustainability (Newman and Kenworthy, 2006), and a number of transport policies for car use reduction have been developed and implemented (Bamberg et al., 2011).

Finding effective measures for car use reduction has long been a challenge for transport policymakers. Car use is attached to symbols of status and power (Gatersleben, 2007), freedom (Freudendal-Pedersen, 2016), pleasure (Wall, 1972) and many other desirable features such as fast, comfortable, and convenient (Gärling and Schuitema, 2007). In a study that explores how car users compare car use and public transport over 17 aspects (comfort, convenience, security, safety and so on), car use was superior to public transport use in almost all aspects except for traffic safety (Steg, 2003b). Goodwin (1997) pointed out that car users have a poor knowledge about alternative transport modes. A recent study revealed that the attitudes toward car use of the travelers in the study seemed to be stable over time from 2014 to 2016 and car use stayed resistant to the effects of changed attitudes toward car use and car ownership (Kalter et al., 2020). Taken together, these facts imply that it is not a straightforward task to make car users switch to alternative modes.

In the literature, various strategies have been proposed to deal with car use reduction. "Hard measures," in which car users are partly forced to reduce car use, are the most popular strategies. Common examples of "hard measures" are pricing, charging, taxation (Marshall and Banister, 2000), or establishments of traffic restricted zones (Elsom, 1997). These interventions affect the monetary value or political power (regulation) of car use (Gärling and Fujii, 2009), which play an important role in the car choice decision process. However, these costly strategies alone failed to achieve their purposes of reducing car use (Bamberg et al., 2011; Möser and Bamberg, 2008). Naturally, "soft measures"—which attempt to stimulate car users to voluntarily switch to other modes of transport—have become an attractive alternative. In "soft measures," interventions are typically made with a focus on psychological factors involved in the decision making process of car users, such as cognitive skills, beliefs, attitudes, and values or norms (Gärling and Fujii, 2009). In practice, the most common "soft measures" are encouragements for changing travel plans, marketing of public transport, and awareness campaigns (Bamberg et al., 2011).

In support of "soft measures" for car use reduction, this study investigated the relationship between environmentalism and car use. Specifically, we attempted to provide an empirical evidence for the intuition that people with positive attitudes toward environmental issues will have a tendency in reducing car use due to the awareness of the environmental consequences from car use. Environmentalism and the awareness of environmental consequences due to human activities are much close issues (e.g., see Section 2.4). That self-awareness can trigger personal norms in reducing one's car uses as a contribution to the efforts in ameliorating the environmental consequences. There are evidence in the literature for the fact that car use reduction behaviors are strongly related to personal norms (Eriksson et al., 2008, 2006; Keizer et al., 2019; Nordlund and Garvill, 2003). A causal effect from environmentalism to car use, if found, can suggest that transport policies should focus more on this measure in car use reduction. Conversely, a non-significant effect would imply that other motivational factors may account for car use reduction, and hence, motivate other researchers to discover these determinants. Empirical evidence in this study thus can contribute to the existing debates on the effects of environmental concerns on behaviors (Donald et al., 2014).

6.2. Data set

To test the relationship between environmentalism and car use, data was extracted from a 2018 online survey in Nagoya city, the third-most-populous urban area of Japan. The city had observed a significant increase in car share from 1971 to 2001 whereas the shares of other modes, such as rail, bus, and walking, have decreased (Sanko et al., 2009). The survey was conducted by the authors of this study with the aim of understanding travel behavior of car users in this city. Attendants of the survey were car drivers in Nagoya city, aged 18 years and above, who were randomly contacted and invited to join a web-based survey. In total, the data was obtained from 900 respondents. The age and sex distribution of the respondents follows that of the population of Nagoya city at the time of the survey. Socio-demographic characteristics of the sample are shown in Table 16. The sample consists of car drivers aged 48 years on average with a quite balanced gender distribution. Notably, more than half of the respondents in our survey were company workers, the population group that seems to undertake more frequent trips (e.g., commute to work) than others.

Table 16. The summary of statistics of the sample in examining the relationship between environmentalism and car use.

Socio-demographic statistics	**Mean (std)**
Age	48.13 (13.61)
Sex (male = 1, female = 0)	0.58 (0.49)
Car number	1.43 (0.68)
Income (10,000 JPY ~ 92.1 USD)	850.63 (3395.8)
Education (number of education years after junior high school)	6.17 (2.43)
Time to the nearest train station (minutes)	10.54 (6.19)
Occupation	**%**
Full-time company worker	52.78%
Full-time public servant	7.44%
Student	1.11%
Part-time worker	11.44%
Housework	11.78%
Unemployed	9.44%
Other	6.00%

Note: std: standard deviation; JPY: Japanese Yen; USD: United States Dollar.

In addition to the socio-demographic characteristics, the respondents were asked to report the facts related to their three most frequent trips. Specifically, the respondents were asked about how frequently they drive in general (e.g., “How often do you drive your own car?”) and they were able to select an answer between “drive sometimes” and “drive often.” The binary responses from this question serve as the first indicator of car use, the “Car_use_1”. Data shows that nearly 70% of the respondents selected the answer “drive often.” Another indicator for car use was obtained by making use of data from their reported trips. From the three reported trips, the frequencies of trips in which a car was used were summed to form a second indicator of car use, the “Car_use_2”. The calculation shows that, on average, the respondents had four trips per week by car.

In the last part of the questionnaire, the respondents were asked to show their agreement/disagreement (five-point Likert scale) with 15 statements included in the revised NEP scale. We selected this scale for measuring environmentalism as it covers the latest trends in the world views on ecological issues, as illustrated in detail in Section 2.4. Considering the respondent's scores between 1 and 5 on a continuous scale, a PCA with VARIMAX rotation was applied to the modified scores where all the scores of the items with negative format (e.g., socially undesirable) had been reversed. The result of the PCA is shown in Table 17.

Table 17. The (modified) average scores of the indicators and factor loadings from PCA's result (run with modified scores) with 2 factors identified in examining the relationship between environmentalism and car use.

		Mean (std)	Factor 1	Factor 2
EN1	We are approaching the limit of the number of people the earth can support	3.47 (0.83)	0.53	
EN2*	Humans have the right to modify the natural environment to suit their needs	3.29 (0.98)		0.69
EN3	When humans interfere with nature it often produces disastrous consequences	3.37 (0.83)	0.52	
EN4*	Human ingenuity will insure that we do NOT make the earth unlivable	2.72 (0.83)		0.46
EN5	Humans are severely abusing the environment	3.8 (0.81)	0.76	
EN6*	The earth has plenty of natural resources if we just learn how to develop them	2.67 (0.84)		0.52
EN7	Plants and animals have as much right as humans to exist	3.89 (0.88)	0.67	
EN8*	The balance of nature is strong enough to cope with the impacts of modern industrial nations	3.32 (0.92)		0.56
EN9	Despite our special abilities, humans are still subject to the laws of nature	3.76 (0.93)	0.68	
EN10*	The so-called "ecological crisis" facing humankind has been greatly exaggerated	3.11 (0.78)		0.58
EN11	The earth is like a spaceship with very limited room and resources	3.6 (0.85)	0.68	
EN12*	Humans were meant to rule over the rest of nature	3.74 (0.98)		0.60
EN13	The balance of nature is very delicate and easily upset	3.7 (0.83)	0.68	
EN14*	Humans will eventually learn enough about how nature works to be able to control it	2.66 (0.81)		
EN15	If things continue on their present course, we will soon experience a major ecological catastrophe	3.57 (0.86)	0.69	
Eigenvalue			4.07	2.06

Note: The asterisk symbol "" means the indicator's scores have been reversed. The factor loadings with absolute values lower than 0.4 are not shown. An eigenvalue cut-off point of 1 is used for determining the number of factors retained.*

Most of the average scores are larger than 3, showing people's tendency towards having high awareness of ecological problems. In addition, the fact that two distinct factors emerged in PCA implies that both Factor 1 and Factor 2 can represent environmental concerns.

6.3. Model specification

To test the possible relationships between environmentalism and car use, SEMs were employed. All possible SEM models are depicted in Figure 15. Three forms of relationships between environmental concerns and car use were modeled, including covariations, unidirectional effects, and reciprocal effects.

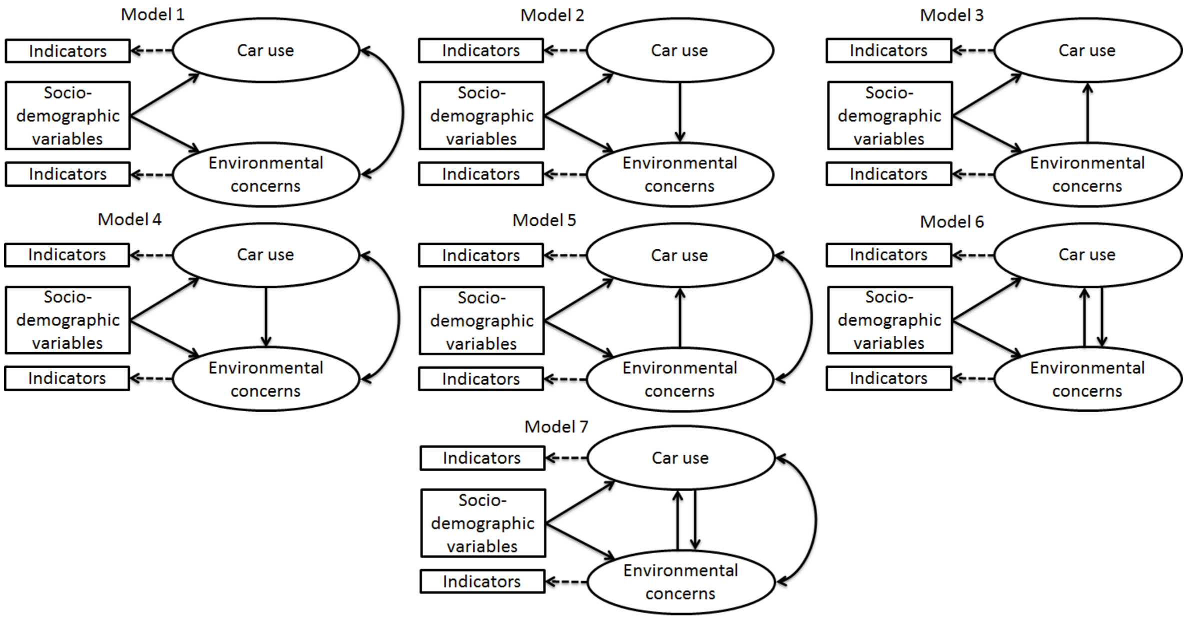

Figure 15. Models for testing the relationship between environmentalism and car use. One-way arrows represent unidirectional effects, whereas two-way arrows denote covariances. Two one-way arrows connecting environmental concerns and car use represent a reciprocal relationship. Dashed arrows show factor loadings from latent variables to indicators

First, a CFA was conducted to verify the goodness-of-fit of measurement models. The result of CFA showed that all the fit indexes were acceptable and all the standardized factor loadings were larger than 0.5. It should be noted that all the indicators are treated as ordered variables as they take on discrete values. This necessitates the application of WLSMV estimator described in Section 3.2.2. In addition, the results of Kline (2016) were followed in model specifications to ensure that SEM models with reciprocal relationships were identified. Finally, all CFA and SEM models were estimated using R (R Core Team, 2018) and the Lavaan package (Yves, 2012).

6.4. Estimation result

The estimation results of seven SEMs where environmentalism are measured by the indicators corresponding to Factor 1 (e.g., EN1, EN3, EN5, EN7, EN9, EN11, EN13, and EN15) are shown in Table 18. It should be noted that similar models built with the set of indicators for Factor 2 (e.g., EN2, EN8, EN10, and EN12) have shown insignificant or behaviorally non-meaningful estimates, and hence, are not being shown here.

Table 18. The unstandardized/standardized estimates and levels of significance of proposed SEM models in examining the relationship between environmentalism and car use.

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
Measurement for car use							
Car_use_1	1/0.93 (N/A)	1/0.95 (N/A)	1/0.93 (N/A)	1/0.93 (N/A)	1/0.93 (N/A)	1/0.94 (N/A)	1/0.93 (N/A)
Car_use_2	2.77/0.78 (**)	2.66/0.77 (**)	2.77/0.78 (**)	2.78/0.78 (**)	2.77/0.78 (**)	2.74/0.78 (**)	2.78/0.78 (**)
Measurement for environmentalism							
EN1	1/0.53 (N/A)	1/0.53 (N/A)	1/0.53 (N/A)	1/0.53 (N/A)	1/0.53 (N/A)	1/0.53 (N/A)	1/0.53 (N/A)
EN3	0.97/0.51 (**)	0.97/0.51 (**)	0.97/0.51 (**)	0.97/0.51 (**)	0.97/0.51 (**)	0.97/0.51 (**)	0.97/0.51 (**)
EN5	1.54/0.8 (**)	1.54/0.8 (**)	1.54/0.8 (**)	1.53/0.81 (**)	1.54/0.8 (**)	1.53/0.8 (**)	1.53/0.81 (**)
EN7	1.25/0.66 (**)	1.25/0.66 (**)	1.25/0.66 (**)	1.25/0.66 (**)	1.25/0.66 (**)	1.25/0.66 (**)	1.25/0.66 (**)
EN9	1.26/0.66 (**)	1.26/0.66 (**)	1.26/0.66 (**)	1.26/0.66 (**)	1.26/0.66 (**)	1.26/0.66 (**)	1.26/0.66 (**)
EN11	1.26/0.66 (**)	1.26/0.66 (**)	1.26/0.66 (**)	1.26/0.66 (**)	1.26/0.66 (**)	1.26/0.66 (**)	1.26/0.66 (**)
EN13	1.31/0.69 (**)	1.31/0.69 (**)	1.31/0.69 (**)	1.31/0.69 (**)	1.31/0.69 (**)	1.31/0.69 (**)	1.31/0.69 (**)
EN15	1.33/0.7 (**)	1.33/0.7 (**)	1.33/0.7 (**)	1.33/0.7 (**)	1.33/0.7 (**)	1.33/0.7 (**)	1.33/0.7 (**)
Causal effects for car use							
Student	-1.17/-0.13 (**)	-1.22/-0.13 (**)	-1.17/-0.13 (**)	-1.07/-0.12 (**)	-1.17/-0.13 (**)	-1.22/-0.13 (**)	-1.06/-0.11 (**)
Car_number	0.3/0.21 (**)	0.31/0.22 (**)	0.3/0.21 (**)	0.26/0.18 (**)	0.3/0.21 (**)	0.3/0.21 (**)	0.26/0.18 (**)
Nearest_train_time	0.03/0.17 (**)	0.03/0.18 (**)	0.03/0.17 (**)	0.03/0.2 (**)	0.03/0.17 (**)	0.04/0.22 (**)	0.03/0.2 (**)
Environmental concerns			**0.02/0.01 (ns)**		**0.05/0.03 (ns)**	**-0.53/-0.29 (*)**	**0.05/0.03 (ns)**
Causal effects for environmentalism							
Company_staff	-0.13/-0.12 (***)	-0.13/-0.12 (**)	-0.13/-0.12 (**)	-0.13/-0.12 (**)	-0.13/-0.12 (**)	-0.14/-0.13 (**)	-0.13/-0.12 (*)
Part_time_job	-0.18/-0.11 (**)	-0.18/-0.11 (*)	-0.18/-0.11 (*)	-0.18/-0.11 (*)	-0.18/-0.11 (*)	-0.19/-0.12 (*)	-0.17/-0.1 (*)
Housework	-0.16/-0.1 (**)	-0.16/-0.1 (*)	-0.16/-0.1 (*)	-0.16/-0.1 (*)	-0.16/-0.1 (*)	-0.17/-0.1 (+)	-0.16/-0.1 (+)
Male	-0.1/-0.1 (**)	-0.1/-0.1 (*)	-0.1/-0.1 (*)	-0.1/-0.1 (*)	-0.1/-0.1 (*)	-0.1/-0.1 (*)	-0.1/-0.1 (*)
Car use		**0.02/0.04 (ns)**		**0.2/0.36 (*)**		**0.17/0.32 (*)**	**0.2/0.36 (*)**
Correlation between car use and environmentalism							
Value	**0/0.01 (ns)**			**-0.17/-0.32 (*)**	**-0.01/-0.02 (ns)**		**-0.18/-0.35 (ns)**
Model fits							
Chi-square	173.69	169.87	173.68	144.40	173.67	147.51	144.38

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
df	97.00	97.00	97.00	96.00	96.00	96.00	95.00
Chi-square/df	1.79	1.75	1.79	1.50	1.81	1.54	1.52
RMSEA	0.03	0.03	0.03	0.02	0.03	0.02	0.02
GFI	0.99	0.99	0.99	0.99	0.99	0.99	0.99
NFI	0.98	0.98	0.98	0.99	0.98	0.98	0.99
CFI	0.99	0.99	0.99	0.99	0.99	0.99	0.99
TLI	0.99	0.99	0.99	0.99	0.99	0.99	0.99
CFI/TLI	1.00	1.00	1.00	1.00	1.00	1.00	1.00
SRMR	0.03	0.03	0.03	0.03	0.03	0.03	0.03
% variance explained for							
Car use	8.30%	8.87%	8.30%	8.27%	8.36%	9.21%	8.25%
Environmentalism	1.62%	1.74%	1.62%	14.50%	1.62%	2.23%	2.43%

Note: (**), (*), (+) and (ns): Significant at 99%, 95%, 90% and not significant at 90% level of confidence; (N/A): This parameter is fixed, and hence, its significance is unavailable; df: Degree of freedom; RMSEA: Root mean square error of approximation; GFI: Goodness-of-fit statistic; NFI: Normed fit index; CFI: Comparative fit index; TLI: Tucker Lewis index; SRMR: Standardized root mean square residual; Socio-demographic variables are dummy coded except for 'Nearest_train_time' measured in minute and 'Car_number' measured in integer; See Section 6.2 for the explanations of items used for measuring car use and environmental concerns.

All the standardized factor loadings are acceptable, which implies strong measurement models, and all the proposed models have good fit indexes, except for the Chi-square statistics. However, Chi-square statistics are sensitive to sample size and, for this reason, judging SEM models based solely on Chi-square statistics is not meaningful (Kline, 2016). Hence, it is possible to make inferences based on the estimates in Table 18. Parallel to testing possible relationships between environmentalism and car use through different model specifications, Chi-square difference tests were conducted for pairs of nested models to specify the best model in terms of data fitting ability. The tests started with the simplest models—Model 1, Model 2, and Model 3— followed by next-level models in the hierarchy, i.e., models formed by allowing an additional path, and hence, an additional parameter—Model 4, Model 5 and Model 6. This model building process (Kline, 2016) results in a system of nested models (e.g., Model 1 is nested in Model 4, Model 6 is nested in Model 7, etc.) and the last model—Model 7—is the most complex model. The results of the Chi-square difference tests are shown in Table 19. Based on the significance of the improvements in Chi-squares when moving from level 1 to level 2 models, only Model 4 and Model 6 outperformed the simplest models. Model 5 was, thus, excluded from the next comparison step. In the next step, moving from level 2 to level 3, Model 7 was found to be not superior to Model 6 and Model 4. The results from the Chi-square difference tests, thus, suggested that Model 4 and Model 6 were the best models. As smaller Chi-square statistics imply better fits to the data, the interpretations from our study were based mainly on the estimates of Model 4.

Table 19. The results of the Chi-square difference tests in examining the relationship between environmentalism and car use.

Level 1	Level 2	Level 3	$\Delta\chi^2$	Δdf	P-value	Significant at 95% confidence level?
Model 1	Model 4		29.29	1.00	0.00E+00	Yes
Model 2	Model 4		25.47	1.00	0.00E+00	Yes
Model 1	Model 5		0.02	1.00	8.88E-01	No
Model 3	Model 5		0.01	1.00	9.20E-01	No
Model 2	Model 6		22.36	1.00	0.00E+00	Yes
Model 3	Model 6		26.17	1.00	0.00E+00	Yes
	Model 4	Model 7	0.02	1.00	8.88E-01	No
	Model 6	Model 7	3.13	1.00	7.69E-02	No

In Model 4, significant negative correlations were observed between environmentalism and car use, at -0.32. It should be noted that, because they are endogenous latent variables, the correlation between them is actually modeled through the correlation between the corresponding error terms. However, the calculation of the corrected coefficient of determination (R2) for endogenous latent variables involved in non-recursive relationships following Hayduk (2006) showed that more than 85% of the variances of these latent variables are due to the variances of the corresponding error terms.[28]

Regarding the causal effects between environmentalism and car use, a significant positive effect of car use on environmentalism was found in Model 4. In the opposite direction, the absence of a significant effect of environmentalism on car use in Model 4 implied the non-existence of this relationship. In fact, this effect was found significant only in Model 6, and it was found insignificant in all other models where it was formulated (e.g., Model 3, Model 5, and Model 7). However, Model 4, which is formed by substituting this effect by a correlation between car use and environmentalism, turned out to better fit to the data than Model 6. These facts are, thus, in line with the Model 4's suggestion of non-existence of the effect of environmentalism on car use.

Finally, the results from all models revealed some important determinants for both car use and environmentalism. Having more cars or living far from train stations was associated with increased car use, whereas students tended to use car less. Similarly, females or people involved in an accident in the past tended to care more about ecological problems, whereas

[28] See Table 3 for the percentages of variances explained by two latent variables in all models. In Model 4, the estimated model accounted for 14.5% of the variance of car use, and hence 85.5% of the variance of car use was due to the variance of the error term of car use.

other occupation categories such as company staff and house workers showed contrary preferences.

6.5. Discussion

In support for transport policies focused on car use reduction, several models which hypothesize different relationships between environmentalism and car use were estimated. All of the proposed models showed acceptable fit indexes and some significant effects were found, from which some discussions can be made.

First, unobserved determinants of environmentalism and car use in this study account for more than 85% of their variances. Interestingly, these unobserved determinants were found to negatively correlate to each other with noticeable correlation coefficient being found. Even though there is no basis on which to infer whether the relationships between these unobserved factors are causal or due to joint sources, or both, it is sufficient to state that these unobserved factors motivate car drivers in our sample to use cars more, but at the same time, it is these factors that discourage them from caring about ecological problems. The identification of these factors can benefit both transport policies, such as reducing car use, and environmental policies, such as raising more awareness of ecological problems. Potential factors that influence both attitudes (e.g., environmental concerns) and behaviors (e.g., car use) may be revealed through examining factors of higher abstract levels, as suggested by the theory of value-attitude-behavior hierarchy (Homer and Kahle, 1988). For example, personal values towards hedonism were found to positively cause attitudes towards flexibility, which in turns had a positive effect on the choices of driving versus public transport (Paulssen et al., 2014). At the same time, hedonic motivations can weaken interests in ecological problems because generally people care about the environment not for pleasure purposes. This example, thus, implies that values towards hedonism may be one of the “hidden” causes of both car use and environmentalism.

In addition, the results from this study showed evidence in support of a causal effect of car use on environmentalism, but not for a causal effect in the opposite way (i.e., from environmentalism to car use). The positive effect of car use on environmentalism, psychologically, can be explained by the intuition that if people use cars more, they may be more aware of the consequence of car use on the environment, and thus, may have stronger environmentalism. In fact, general attitudes (e.g., environmentalism) can be formed by three elements: feelings, beliefs, and past behavior and these elements can be obtained by direct experience with objects (Maio et al., 2003). In this case, direct experience with car use was found to enhance general attitudes towards ecological problems. This unexpected effect, arguably caused by a specific sample consisted of only car drivers, signified the need for more empirical evidences. At the same time, only a significant negative effect of environmentalism on car use was found in Model 6, which is in line with Bouscasse et al. (2018), Donald et al. (2014) and Roberts et al. (2018), whereas the overall implication from all the analyzed models was a non-existence of this effect. Social dilemmas and cognitive dissonance, as discussed in Section 2.2, can be two possible explanations for this fact. This finding suggests that soft measures for car use reduction that focus on changing people's awareness of ecological problems may not be an effective solution for transport policymakers.

Finally, this study illustrated the usefulness of reciprocal relationships in SEMs. Model 6 and Model 7, for example, are the models among those with the lowest Chi-square statistics. Such models would have not be revealed if reciprocal relationships had not be modeled. Thus, reciprocal relationships should be considered in relating latent variables whenever possible, as they may be helpful in identifying the models that best fit the data.

6.6. Conclusions

In this study, we attempted to find any possible effect of environmentalism on car use behaviors. Several SEMs with environmentalism, car use variable, and other socio-demographic variables were estimated using data from a sample with 900 respondents from Nagoya, Japan. All the estimated models showed good fit measures and a Chi-square difference test helped to identified the best models in terms of fitting the dat. Unobserved determinants of environmentalism and car use in this study accounted for more than 85% of their variances. A significant negative correlation was found between environmentalism and car use, whereas the coefficient representing for the unidirectional effect of environmentalism on car use was found being insignificant. Thus, we found the relationship between environmentalism and car use is mainly due to negative correlation and there is no unidirectional causal effect of environmentalism on car use behavior being found. In addition, there may exist hidden causes of both environmentalism and car use behaviors that if identified can be examined in designing environmental and transport policies. Thus, we suggest future soft measures for car use reduction to focus on factors other than socio-demographic and environmentalism.

Chapter 7: The effect of APA on bus use intentions

7.1. Introduction

In this chapter, travel intention, an immediate determinant of travel behaviors, was of our interest. In practice, examining the determinants of travel behaviors is not always a straightforward process if the behaviors in question are rare. In addition to the bias imposed on the model estimates due to data separation, as illustrated in Section 3.1.5, the rarity of the behavior implies a corresponding weak measurement model which, as a result, can suppress the manifestation of the relationships between behaviors and their determinants. Considering the fact that intentions were considered immediate and important determinants of behaviors in several behavioral theories well known in transport studies, such as TRA/TPB (Ajzen, 1991; Ajzen and Fishbein, 1980; Fishbein and Ajzen, 1975), the theory of interpersonal behavior (Triandis, 1977), and the model of goal-directed behavior (Perugini and Bagozzi, 2001), studying the determinants of intentions can be a suitable proxy for understanding infrequent behaviors.

In this studies, we examine the effect of APA on bus use intentions (BUI). As evidence on the association between physical activity and public transport use can be found in research (Rissel et al., 2012), it is possible to hypothesize a positive effect of APA on BUI. However, we did not find any previous studies that confirm this effect. A study on teenagers' travel-to-school mode choice (Kamargianni et al., 2015) is the only case in the literature that considers APA in a travel context, but this study is concerned with mode choice behaviors, rather than intentions. We also attempt to determine how both individuals' sociodemographic characteristics and built environment variables moderate the hypothesized effect from APA to BUI.

7.2. Data set

The data set used in this study comes from a Mobility Management (MM) campaign conducted in Asuke, a small Japanese town now part of Toyota City. The characteristics of Asuke and the description of its bus system can be found in Section 5.3.

We used a questionnaire designed to capture the sociodemographic characteristics of respondents and their evaluations through questions aimed at their specific attitude toward bus use, Subjective Norms (SN), Perceived Behavioral Controls (PBC), APA, and BUI. We used a single indicator ("I love to use the CB") designed to assess their specific attitudes toward bus use. The SN for bus use was measured by three indicators that reflected the individual's perceived societal pressures to use the bus. These pressures can come from the perception that public transport benefits both the community and the individual citizen. For the indicator of PBC for bus use, we asked respondents how well they know the bus system's operations. Given the low frequency and limited number of routes for the local bus system in Asuke, we assumed that the lack of knowledge about bus fares, timetables, and routes discourages people from intentions to use the bus. To measure APA, two indicators, that represent the respondent's evaluation on the importance for their health of walking and going out (e.g. not staying at home) were used. The BUI was measured by three indicators in both direct and indirect ways (e.g. by asking respondents how their schedules will be affected by bus use). A five-point Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree) was used for all the indicators, except the question about the knowledge of bus use. To assess how well people knew the bus timetables and routes, the respondents were required to select one among five statements, arranged in a decreasing order of knowledge. Then, their answers were reversed so that the modified responses followed an increasing level of bus use knowledge.

In the MM program, questionnaires (in Japanese) were distributed to a total of 2,838 households in Asuke in September 2017, and 1,009 households responded by October 2017. In total, 2,352 residents answered the questions. However, as the questionnaires were mailed, many people did not complete all the required items. After excluding the cases with incomplete information, a total of 1,604 questionnaires were analyzed.

The statistics of the sociodemographic characteristics of the respondents are summarized in Table 20.

Table 20. Sociodemographic characteristics of respondents (N = 1604) in examining the effect of APA on BUI.

Feature	Category	Percentage	Mean	SD
Gender	Male	49.69%	-	-
	Female	50.31%		
Age (years)	<20	2.93%	60.14	18.50
	20 ~ 29	4.99%		
	30 ~ 39	7.42%		
	40 ~ 49	10.6%		
	50 ~ 59	16.08%		
	60 ~ 69	27.93%		
	70 ~ 79	14.03%		
	80 ~ 89	13.03%		
	>90	2.99%		
Time to the nearest bus stop (minutes)	≤5	76.37%	8.36	50.63
	6 ~ 10	14.28%		
	11 ~ 15	3.3%		
	16 ~ 20	2.56%		

Feature	Category	Percentage	Mean	SD
	21 ~ 25	0%		
	> 25	3.49%		
Usual transport mode	Car (Driven by me)	57.63%		
	Car (Driven by family, etc.)	26.74%		
	Motorcycle or moped	4.42%		
	Bicycle	6.07%		
	Three-wheeled car	0.85%		
	Other	4.29%		
Occupation	Company employee, company management	24.19%		
	Public servant/group staff	7.11%		
	Student	3.30%		
	Part-time job	15.15%		
	Housewife/househusband	13.03%		
	Agriculture/forestry	6.80%		
	Unemployed	25.56%		
	Other	4.86%		

The average age of the sample was 60.14 years. Compared with the average age of 52.81 of the Asuke population, this statistic indicates a high portion of elderly people in the sample. A noticeable statistic is the distance (in time) to the nearest bus stop. Nearly half of the respondents live within five minutes of a bus stop, and approximately 80% of them are within ten minutes of a bus stop. The sample shows an equal distribution between males and females, similar to the Asuke population, while the occupation statistic identifies two main groups—company staff (24.19%) and unemployed people (25.56%). The portion of respondents with a job, in our sample, accounts for 53.25% of the total sample and this is similar to the occupation distribution of the Asuke population. The car is the most common mode of the sample. The total portion of people who drive themselves or who are driven by a relative was approximately 84.38%. The information collected in the sample reflects the typical situation of the low effectiveness of the bus system in Asuke.

The means of respondents' scores in psychological indicators is given in Table 21. Generally, respondents in the sample had fairly high APA but not strong BUI. The t-tests of unequal sizes and unequal variances, comparing the means of APA and BUI of several socio-demographic groups, revealed some interesting facts. At the 95% level of confidence, we found no difference in the means of APA of male and female groups. However, the mean of APA of the elderly male group (≥ 70 years old) was significantly larger than that of the young male group (< 70 years old)—the difference was 3.27%. This implies that for this male group, an increase in APA was associated with an increase in their ages. The mean of BUI of the female group (3.14) was significantly larger than that of the male group (3.02), and this fact is intuitive as, generally, females have lower access to cars than males have. In both the male and female groups, the means of BUI of elderly respondents (3.38 and 3.47) were significantly larger than those of younger respondents (2.87 and 2.99). In other words, an increase in the respondents' ages was associated with an increase in their BUI. Finally, the mean of BUI of the female non-driver group (3.34) was significantly larger than that of the female self-driver group (3.07).

Table 21. EFA results for the indicators in examining the effect of APA on BUI.

No	Factor	Indicators	Corresponding question	Mean (Standard Deviation)	PCA factor loading	Cronbach's alpha
1	Attitude toward physical activity (APA)	APA1	Walking is good for your health.	4.47 (0.81)	0.86	0.63
		APA2	Going out (e.g. not staying at home) is useful for maintaining your health.	4.27 (0.89)	0.86	
2	Attitude toward bus use (ATT)	ATT1	I love to use the CB.	2.44 (1.13)	-	-
3	Subjective norms (SN) for bus use	SN1	Improving public transport, more than now, will enrich your family's life.	3.53 (1.23)	0.89	0.79
		SN2	The town will flourish as public transport improves.	3.74 (1.13)	0.85	
		SN3	I feel inconvenienced by daily traffic.	3.09 (1.49)	0.77	
4	Perceived behavioral control (PBC) of bus use	PBC1	How well do you know the bus fares, routes, and timetable[29]?	2.37 (1.00)		
5	Bus use intention (BUI)	BUI1	I plan to use CB more.	2.94 (1.2)	0.87	0.78
		BUI2	My life is inconvenient if CBs are unavailable.	3.38 (1.37)	0.84	
		BUI3	I can reorganize my daily schedule according to public transport schedules.	2.95 (1.27)	0.79	

The measurement model showed acceptable fit measures and suitability for SEMs. All the Cronbach's alphas are greater than 0.5, showing potential for good internal consistency among the indicators (Kline, 2011). Thus, the next step was to verify the measurement model using a CFA approach. Before being submitted to the CFA, the input data was checked to ensure that it was suitable for the CFA. We employed MLE for CFA (and SEM) as MLE is asymptotically unbiased in large samples and is a consistent and efficient estimator (Bollen, 1989). Additionally, the Mardia's test (Mardia, 1970) for the multinormality of the observed variables was conducted by using the MVN package (Korkmaz et al., 2014) in the R system for statistical computing (R Core Team, 2018). The results show that the test statistic for

[29] The answers for this question were numbered from 1 to 5 and arranged in a decreasing level of knowledge about buses' timetables and routes, such as "I'm familiar with the routes and timetable" or "I know little of the fare, routes, and timetable."

Mardia skewness is 1133.4 (P-value = 0), and for kurtosis it is 14.51 (P-value = 0). The observed variables were, thus, statistically not multivariate normally distributed. To account for the non-normality of the input data, bootstrapping was embedded into the MLE estimation process to calculate the standard errors (Finney and DiStefano, 2013). The estimation for CFA was done by using a SEM package (Yves, 2012) in the R system for statistical computing (R Core Team, 2018). Note that, in this study, we considered the indicators as continuous variables. The CFA models (run with the second half of the total sample) showed quite a good fit with the observed data. All the factor loadings were significant, with the values ranging from 0.54 to 0.91 (standardized solution) for both the base and the extended TPB models. All the fit indexes were acceptable: the chi-square (with the degrees of freedom in brackets) $\chi^2_{(25)}$= 109.43 (P-value = 0); χ^2/df =4.38; RMSEA = 0.06; GFI = 0.97; NFI = 0.95; and CFI = 0.96 for the extended TPB model and $\chi^2_{(4)}$= 10.89 (P-value = 0.03); χ^2/df = 2.72; RMSEA = 0.05; GFI = 0.99; NFI = 0.99; and CFI = 0.99 for the base model (see the note under Table 4 for the fit index abbreviations listed above).

7.3. Model specification

In this study, we designated three TPB's variables as mediators for the effect of APA on BUI. TPB is a common behavioral theory that models the relationships between (specific) attitudes and behavioral intentions (see Section 2.2.2 for more details). In the literature, attitude-mediator-intention models have been supported with suggestions that (general) attitudes should influence the subsequent behaviors and intentions indirectly through the constructs that are closer to these behaviors (Ajzen, 1991; Ajzen and Fishbein, 1973; Bamberg, 2003; Fishbein and Ajzen, 2009), and with empirical studies such as in the case of environmental concerns and the intention to visit green hotels (Chen and Tung, 2014); environmental concerns and the intention to use a park-and-ride facility (transferium) (de Groot and Steg, 2007); and environmental concerns and the intention to use public transportation (Borhan et al., 2014). In light of this, we considered the general attitude-specific attitude relationship, that was illustrated in Section 2.3, and the specific attitude-intention relationship under TPB model, that was made detailed in Section 2.2.2, in developing our model framework shown in Figure 16.

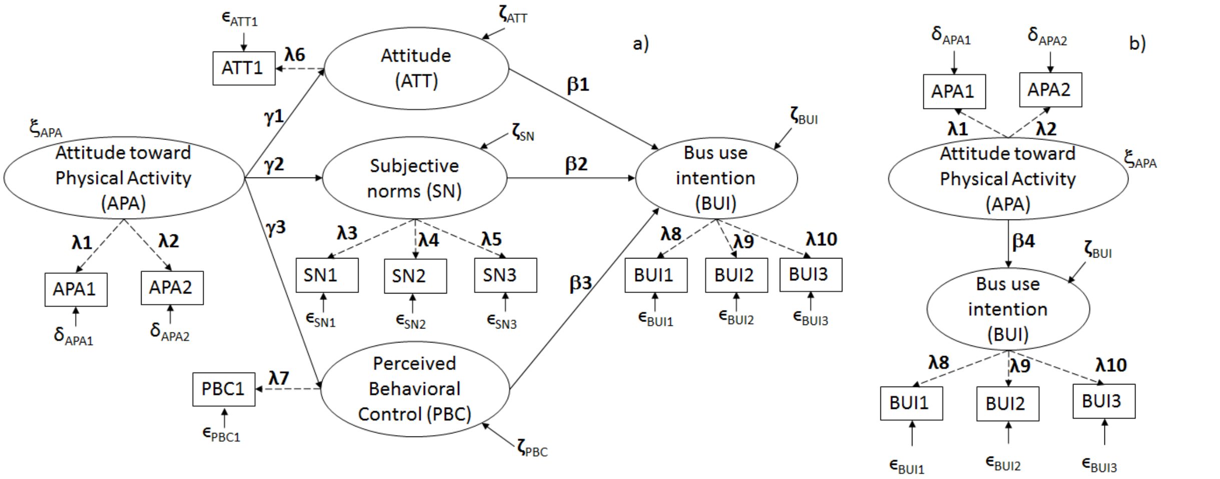

Figure 16. The extended TPB model (a) and the base model (b) in examining the effect of APA on BUI. The notation follows (Bollen, 1989)

To make SEMs identifiable, we placed several constraints following the instructions in Bollen (Bollen, 1989) and Kenny et al. (Kenny et al., 1998). Specifically, the error terms of the observed variables were assumed to be uncorrelated with each other and latent variables. The scales of latent variables were specified by setting both variances of exogenous latent variables and variances of error terms of endogenous latent variables to 1 (in case of standardized solution) or by constraining the factor loading of the first indicator of every construct to 1 (in case of unstandardized solution). Note that we did not treat the two constructs, attitude toward bus use (ATT) and perceived behavioral control (PBC), with single indicators as directly measured, such as in Shen & Takeuchi (Shen and Takeuchi, 2001) and Donald et al. (Donald et al., 2014). Instead, we formulated these constructs as single-indicator latent variables. In addition, the residual variances of these single indicators were not constrained to any fixed values. In this way, the score reliabilities of these single indicators were estimated by the model rather than being fixed (Bollen, 1989). This step helps to overcome the weakness of using single indicators in SEM.

In addition, the mediating effects of several exploratory variables, as shown in Table 20, on the hypothesized causal effects in our models, were investigated by employing a multiple-groups SEM framework (Bollen, 1989; Kline, 2011). Although multiple-group analysis enabled the test for several levels of invariance in SEM (e.g. form invariance, regression coefficient invariance, factor loading invariance, and so on), we restricted this analysis to the test of equality in parameters (regression coefficients) across groups. The multiple-groups analysis was carried out in which the sample grouping is based on characteristics listed in

Table 20 (e.g. the full sample is split into a 'car driver' subsample and a 'non-car driver' subsample).

7.4. Estimation result

After the measurement models were verified with CFA and showed suitability, the proposed models were then estimated by SEM with the full dataset (1,604 respondents). The estimates and the fit indexes for the extended TPB model and base model are presented in Table 22 and Table 23. Note that only the results from the multiple-groups analysis, for the compared groups in which their effects from APA to BUI are statistically different at 95% level of confidence, are presented.

In the extended TPB model, the three TPB variables—ATT, SN, and PBC—were found to positively affect BUI with significant regression coefficients ranging from 0.36 to 0.98 (standardized). In addition, the unstandardized effect (in terms of regression coefficient) of APA to BUI in the extended TPB model was 0.79. Compared with the unstandardized effect, in the case of direct relation between APA and BUI in the base model at 0.65, the moderators helped to increase the regression coefficient for this relation by 21.5%. Another advantage of employing TPB variables, as mediators for the effect of APA on BUI, is the improvement in the model predictability for BUI. The percentage of variance of BUI, explained by the extended TPB model, is 64.4% while the base model can only account for 8.6% of the variance.

Table 22. Estimates of the extended TPB model and the base model for the whole sample and for the compared groups in examining the effect of APA on BUI.

Extended TPB model								**Base model**
From ↓ **To**	APA ↓ ATT	APA ↓ SN	APA ↓ PBC	ATT ↓ BUI	SN ↓ BUI	PBC ↓ BUI	APA ↓ [a)] BUI	APA ↓ BUI
All sample	0.59/*0.32* (0.006)**	0.99/*0.5* (0)**	0.47/*0.31* (0.004)**	0.59/*0.98* (0)**	0.3/*0.51* (0)**	0.3/*0.36* (0)**	0.79/*0.68*	0.65/*0.31* (0)**
≥ 70 years old	2.76/*1.83* (0.074)	2.34/*0.75* (0.007)**	2.19/*1.01* (0.064)	0.76/*0.8* (0)**	0.11/*0.21* (0.355)	0.32/*0.2* (0)**	N/A	These groups were found as statistically equal in effect from APA to BUI
< 70 years old	0.4/*0.22* (0)**	0.9/*0.45* (0)**	0.33/*0.24* (0)**	0.58/*0.93* (0)**	0.32/*0.55* (0)**	0.2/*0.26* (0.004)**	0.58/*0.52*	
Unemployed	2.26/*1.26* (0.15)	2.11/*0.85* (0.03)*	1.86/*0.86* (0.136)	0.62/*0.78* (0.001)**	0.24/*0.37* (0.052)	0.29/*0.26* (0.01)**	N/A	
Employed	0.48/*0.26* (0)**	0.96/*0.45* (0)**	0.38/*0.25* (0)**	0.63/*1.04* (0)**	0.29/*0.54* (0)**	0.27/*0.33* (0)**	0.69/*0.6*	
Car user[b)]	0.45/*0.24* (0.001)**	0.93/*0.46* (0)**	0.35/*0.27* (0)**	0.58/*0.9* (0)**	0.31/*0.55* (0)**	0.26/*0.33* (0.01)**	0.64/*0.56*	
Non-car user	1.42/*0.77* (0.098)	1.39/*0.73* (0.017)*	1.26/*0.67* (0.152)	0.68/*1.02* (0)**	0.2/*0.28* (0.094)	0.34/*0.36* (0.02)*	N/A	

Extended TPB model								Base model
From ↓ To	APA ↓ ATT	APA ↓ SN	APA ↓ PBC	ATT ↓ BUI	SN ↓ BUI	PBC ↓ BUI	APA ↓ [a)] BUI	APA ↓ BUI
> 5 minutes [c)]	0.31/*0.2* (0.64)	0.64/*0.39* (0.319)	0.5/*0.46* (0.297)	0.8/*1.05* (0)**	0.22/*0.37* (0.021)*	0.41/*0.54* (0.065)	N/A	
≤ 5 minutes	0.69/*0.34* (0.006)**	1.11/*0.52* (0)**	0.44/*0.25* (0.017)*	0.54/*0.94* (0)**	0.33/*0.56* (0)**	0.26/*0.3* (0)**	0.85/*0.68*	

*Note: ** p-value < 0.01; * 0.01 < p-value < 0.05;* ***a)*** *The total indirect effects of APA on BUI, in the extended TPB models, are calculated from significant (p-value < 0.05) direct effects;* ***b)*** *Respondents who selected the car as their usual transport mode, are considered car users;* ***c)*** *This denotes respondents who reported a distance of more than five minutes from the nearest bus stop;* ***N/A****: Calculation for this indirect effect of APA on BUI was not possible due to the insignificance (p-value >0.05) of the direct effects; From left to right: unstandardized estimates, standardized estimates (written in italics), and p-values (in the parentheses); From left to right: unstandardized estimates, standardized estimates (in italics), and p-values (in the parentheses); The standard errors (which determine the corresponding p-values) were calculated by using unstandardized scores of observed variables* (Bollen, 1989).

Table 23. Model fit indexes of the extended TPB model and the base model for the whole sample and for the compared groups in examining the effect of APA on BUI.

Sample/Group	% variance explained for BUI	Group χ^2	Total χ^2	Df	χ^2/df	RMSEA	GFI	NFI	CFI	Sample Size
Extended TPB model										
All sample	64.4%		370.05	29	12.76	0.09	0.95	0.92	0.93	1604
≥ 70 years old	80.1%	148	379.28	58	6.54	0.08	1.00	0.92	0.93	482
< 70 years old	60.1%	231.27								1122
Unemployed	75.7%	169.88	385.55	58	6.65	0.08	1.00	0.92	0.93	410
Employed	64.7%	215.68								1194
Car user	60.5%	269.31	368.64	58	6.36	0.08	1.00	0.92	0.93	1291
Non-car user	73.3%	99.33								313
> 5 minutes	65.5%	152.03	427.48	58	7.37	0.09	0.99	0.91	0.92	379
≤ 5 minutes	63.6%	275.45								1225
Base model										
All sample	8.6%		11.43	4	2.9	0.03	1.00	0.99	1.00	1604

Note: From left to right: ***% variance explained for BUI****: The ability of the model to account for the variance of BUI, calculated by the standardized solution;* ***Group χ^2****: The amount of chi-square for each group of the estimated two-groups SEM;* ***Total χ^2****: The chi-square test statistic to assess the overall goodness of fit of both the two-groups SEM and normal SEM;* ***Df****: The degree of freedom of the model;* ***RMSEA****: The root mean square error of approximation;* ***GFI****: The goodness-of-fit statistic;* ***NFI****: The normed fit index;* ***CFI****: The comparative fit.*

The estimates of the extended TPB models, with data from compared groups, revealed some interesting facts. Regarding the estimates by age group, only the differences in the estimates of the extended TPB model for respondents aged 70 years and older, and those for the younger respondents, are significant. Observing the estimates of the extended TPB models for these two groups more deeply, APA does not seem to be a strong motivation for the BUI for the older group—an indirect link between these two factors could not be established at the 95% level of confidence. However, if a less restrictive criterion, based on the threshold of p-value considered to be significant (e.g. less than 0.1 rather than 0.05) is applied, then the indirect effect of APA on BUI can still be found for this group (mediated by ATT and PBC, not by all the TPB's variables as with the younger groups). For the younger group, the highly significant estimates strongly suggest that this group views APA as a real motivation for the intention to use the bus. This view can also be found for the unemployed group and the not-unemployed group. While the effect of APA on BUI is only mediated by SN for the former group, if a threshold of p-value at 0.052 is considered significant, the latter group shows the highly significant role of APA in causing the intention to use the bus. The final comparisons reveal a similar pattern for car users and people living within five minutes of the nearest bus stop, both groups have strong physical activity motivation for BUI. However, the link between APA and BUI for non-car users can only be established at the 90% level of confidence and is unavailable for people who live more than five minutes from the nearest bus stop. One important fact must be noted here—the sample sizes of the compared groups. Most of the cases of lower significances of the estimates are with groups of smaller sample size. This finding implies that small sample sizes can be a cause of the insignificant estimates from SEM and, thus, a larger sample size would strengthen the belief that APA has an effect on BUI. Apart from the above four cases, we found no statistically significant differences in the estimates of the extended TPB models for other pairs of groups, such as models for males versus females.

7.5. Discussion

In this study, we examining the effect of APA on BUI using the extended TPB model and with data of respondents living in Asuke, Japan. Significant effects were found in our postulated models which led to two main findings as follows.

First, the results from the base model and the extended TPB model provide supportive evidence for the causal effect of APA on BUI. In addition, the improvement in modeling the effects of APA on BUI, brought about by the introduction of the TPB's variables as mediators, is in line with the suggestion in (Bamberg, 2003) that general attitudes influence subsequent behaviors indirectly. From a transport policy perspective, this finding suggests that BUI can be increased if promotion campaigns increase people's APA, attitude toward bus use, SN, and PBC for bus use. As intention is the most immediate and important predictor of behavior (Sheeran, 2002), the increased BUI can lead to increased bus use, which is important for mitigating physical inactivity in rural areas, partly caused by car dependence. This finding can also be seen as a supportive argument for the idea of combining transport policies with health polices—the existing literature suggests that combining mobility and physical activity offers a cheap, feasible strategy for increasing a large population's physical activities (Götschi et al., 2016).

Second, we also found significant differences in the patterns of effects among several pairs of groups. First, for younger people, preferences in physical activity are likely to prevail in their subsequent physically active behaviors; in the case of bus use, these interests (along with other factors such as SN and PBC) can positively bias their attitudes toward bus use as they seek to maintain physical health. For elderly people, although these causal relations are not as clear as for younger people, and the effect of SN on BUI is strongly insignificant, the same expectation can be made with a little relaxation of the significance threshold. This implies that promotion campaigns for raising APA, in order to increase BUI, can be effective with the elderly. Another noticeable finding is the strong effect of APA on BUI of car users. As car dependency is generally high in rural areas, and motivating public transport use is not straightforward, this finding suggests an alternative measure of intervention—promoting modal shifts for car users by increasing awareness of the benefits of physical activity. Finally, as only respondents living close to a bus stop are associated with significant effects of APA on attitudes toward bus use, SN, and PBC—as opposed to respondents of longer distance—transport policy interventions, to promote bus use through changing the built environment, should be evaluated. That is, efforts to increase bus ridership by improving people's attitudes toward physical activity can be effective only for respondents living near bus stops. Thus, we suggest that among the efforts in improving the built environment for walking and cycling, solutions for reducing walking distances to bus stops (e.g. by placing more bus stops along bus routes) should be given higher priority. This, combined with promotion campaigns to improve people's attitudes toward physical activity, will potentially lead to an increase in bus ridership, along with the expected improvements in accessibility to bus use.

7.6. Conclusions

This study was concerned with the effect of APA on BUI, an immediate determinant of bus use. We postulated a mediation model for APA-BUI relationship which is based on TPB and the general-specific attitude relationship mentioned in Section 2.3. SEMs and multiple-group analysis were conducted using data collected in Asuke, Japan. In both extended TPB model and Base model, we found significant indirect and direct regression coefficients of APA on BUI. The mediators helped to both raise the regression coefficients and improve the model ability to account for the variance of BUI. The multiple-groups analysis further revealed that the coefficients are significant for several groups, such as young people, employed people, and car users. Thus, this study confirmed the effect of APA on BUI, in both direct and indirect ways. The effect, however, varies for different groups. In line with the previous results in case studies in Chapter 4 and Chapter 5, we suggest that APA should be a significant determinant of travel intentions. Further, TPB's variables can serve as a good mediator for the effects of general attitudes on travel intentions (and behaviors).

Chapter 8: Conclusions and future directions

8.1. Conclusions

This dissertation was an effort of confirming the effects of environmentalism and APA on travel behaviors. We employed the frameworks of choice models and SEMs in verifying the examined effects with two data sets collected in Japan. Environmentalism was found to be associated with an increase in the mode share of rail in the LCC model. Unexpectedly, only a significant negative correlation between environmentalism and car use was observed, whereas the coefficient representing for the unidirectional effect of environmentalism on car use was found being insignificant. Unobserved determinants of environmentalism and car use accounted for more than 85% of their variances. For APA, we found both significant coefficients in the utility functions of bicycle and walking, and in the membership function of the LCC model. We also found a significant regression coefficient of APA on ATT_B in both models for clinic/hospital trips and for shopping trips, and a significant coefficient representing for the effect of ATT_B on the bus utility. In both extended TPB model and Base model, we found significant indirect and direct regression coefficients of APA on BUI. The TPB mediators helped to both raise the regression coefficients and improve the model ability to account for the variance of BUI. The multiple-groups analysis further revealed that the coefficients are significant for several groups, such as young people, employed people, and car users. Additionally, we observed higher cares for private benefits than cares for environmental issues in the Nagoya sample. In terms of methodological implications, the latent class framework was useful in unraveling the effect of environmentalism on mode choice that is frequently reported as insignificant in previous studies. We found very large biases in the estimates and standard errors of the binary choice models under a highly unbalanced mode share pattern. The Firth bias correction method significantly reduced these biases, leading to some improvements.

This dissertation thus confirmed that environmentalism has an indirect effect on the choices of rail, a form of mass transit. The relationship between environmentalism and car use was found being mainly due to negative correlation, and there is no unidirectional causal effect of environmentalism on car use behavior being found. On the other hand, the effects of APA on both mode utility and mode choice of bicycle and walking were confirmed. The effects of APA on mode choice were further confirmed in a context of a highly unbalanced mode share pattern. This dissertation also confirmed the effect of APA on BUI, in both direct and indirect ways. The effect, however, varies for different groups. Thus, we strongly suggested an idea of combining transport policies with environmental and health policies so as the maximize their influences on the society through the factor environmentalism and APA. Following the discussions in Section 2.1, this can be done by intervention campaigns targeting at changing attitudes. Repeatedly exposing to advocate messages, i.e. the importance of physical activities, can cause people to change their beliefs/evaluations about the attitude objects, i.e. from 'not so important' to 'important', that ultimately leads to improved attitudes. Both EML and HSM models suggest that the effectiveness of these campaigns depends much on how people process the advocate messages. Thus, we suggest the implementations of these campaigns to pay attention on how to cause people to spend more time in interpreting the messages or interventional information (e.g., strategies to induce more processing time). For policies of car use reduction, we suggest against environmentalism as an intervened object due to its insignificant effect. In addition, there may exist hidden causes of both environmentalism and car use behaviors that, if identified, can be helpful in designing environmental and transport policies. Thus, we suggest future soft measures for car use reduction to focus on factors other than socio-demographic and environmentalism. Finally, we suggested that APA can be intervened in promoting bus use in rural areas.

For the literature in travel behavior analysis, we suggested that environmentalism and APA should be appended to the list of travel behavior determinants. The LCC model framework is helpful in accounting for the taste heterogeneities and, thus, being suggested for exploring the effects of latent variables on mode choice models. The Firth bias method is also suggested as a solution for the issue of data separation that is likely to occur in highly unbalanced mode share patterns. Finally, TPB's variables can serve as a good mediator for the effects of general attitudes on travel intentions (and behaviors).

8.2. Future directions

In this section, we propose some potential directions for future studies in travel behaviors based on the findings from our four case studies. The proposals presented here come from both limitations in our study and from some potential outcomes revealed when we explored the issues in each case study.

First, we suggest future studies to consider the effects of environmentalism and APA on mode choice models of different choice sets. In our empirical case studies in Chapter 4 and Chapter 5, the observed mode shares are skewed highly toward car use and as a result, some alternatives could not be considered (e.g., bus use). Thus, future studies can expand the choice sets to other modes that are potentially influenced by the two constructs. By that, the effects of environmentalism and APA on mode choice behaviors will be confirmed with more modes considered and, hence, expanding the influential ranges of policy interventions.

Second, we highly suggest the LCC model framework for studying latent variable models, particularly when the effects of some latent variables are not clear enough to be explored by the ICLV model. If more heterogeneity is accounted for, then the increased number of parameters can help revealed some hidden relationships. Clearly, the number of classes is not restricted to two as in our study, and can be specified by trading-off between the stability of the estimates and the information obtained.

Third, we suggest future studies to check for data separation whenever mode shares are highly unbalanced and categorical covariates are used. Some detection methods have been used in our study, such as the use of two-way contingency table and the use of estimation software. In case data is separated, Firth bias correction method can be a solution for binary logit choice model. The potential of this method in reducing standard errors and ensuring the existence of MLE estimates has been proven and verified in our study. The limitation of the estimation software used in this study can be overcome by the future advancements that allow for simultaneous estimation processes. In these case, the power of this method will be strengthened.

Forth, in promotion for positive APA, we advocate for more studies in rural areas in developed countries employing APA as a determinant of travel intentions and behaviors. Targeting on APA has a proven potential in reducing physical activity inequality in these areas, which contributes to ensuring social justice.

Fifth, we suggest future policies in car use reduction to focus more on factors other than common socio-demographic characteristics and environmentalism. The identification of these factors may provide more insights into the relationship between environmentalism and car use, and thus, help transport policy makers design effective interventions on car use reduction. In model specifications, we also suggest allowing for reciprocal relationships and correlation among latent variables as it helps to identify the best models.

Sixth, we suggest future studies to use other forms of mediators for the attitude-intention relationships. There are still debates on the effects of general attitudes and behavioral intentions and behaviors. Employing other forms of mediation can help shedding a light on these loose relationships from which the roles of general attitudes in analyzing travel behaviors can be enhanced.

Finally, we suggest the use of single-indicator latent variables in SEMs instead of treating these indicators as observed variables or placing some restrictions on their reliabilities. This trivial practice can bring some enhancements for measurement models in SEMs.

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Appendix A. Checking for data separation example

The checking for data separation in the three cases in Figure 7 that follows Eq. 28 and Eq. 29 is described in Table 24 below.

Table 24. Checking for data separation for three cases a), b), and c) in Figure 7.

Case	Group (j)	Number of observations	Y (j)	x_0	x_1	α_j	x_i	$(\alpha_j - \alpha_t)^T x_i$	Checking
a) Complete separation	1	3	0	1	1	$\begin{bmatrix}-1\\2\end{bmatrix}$	(1;1)	$\left[\begin{bmatrix}-1\\2\end{bmatrix}-\begin{bmatrix}0\\0\end{bmatrix}\right]^T * \begin{bmatrix}1\\1\end{bmatrix} = 1$	$(\alpha_j - \alpha_t)^T x_i > 0$ for all i ∈ (1;2)
	2	4	1		0	$\begin{bmatrix}0\\0\end{bmatrix}$	(1;0)	$\left[\begin{bmatrix}0\\0\end{bmatrix}-\begin{bmatrix}-1\\2\end{bmatrix}\right]^T * \begin{bmatrix}1\\0\end{bmatrix} = 1$	
b) Quasi-complete separation	1	2	0		1	$\begin{bmatrix}0\\1\end{bmatrix}$	(1;1)	$\left[\begin{bmatrix}0\\1\end{bmatrix}-\begin{bmatrix}0\\0\end{bmatrix}\right]^T * \begin{bmatrix}1\\1\end{bmatrix} = 1$	$(\alpha_j - \alpha_t)^T x_i \geq 0$ and equality happens correctly for all i ∈ (1;2)
		1			0		(1;0)	$\left[\begin{bmatrix}0\\1\end{bmatrix}-\begin{bmatrix}0\\0\end{bmatrix}\right]^T * \begin{bmatrix}1\\0\end{bmatrix} = 0$	
	2	4	1		0	$\begin{bmatrix}0\\0\end{bmatrix}$	(1;0)	$\left[\begin{bmatrix}0\\0\end{bmatrix}-\begin{bmatrix}0\\1\end{bmatrix}\right]^T * \begin{bmatrix}1\\0\end{bmatrix} = 0$	
c) Overlap	1	2	0		1	$\begin{bmatrix}a\\b\end{bmatrix}$	(1;1)	$\left[\begin{bmatrix}a\\b\end{bmatrix}-\begin{bmatrix}0\\0\end{bmatrix}\right]^T * \begin{bmatrix}1\\1\end{bmatrix} = a + b$	No non-zero values for a and b satisfy *both* (a+b>0), (a>0), (-a-b>0), and (-a>0), *or both* (a+b≥0), (a≥0), (-a-b≥0), and (-a≥0).
		1			0		(1;0)	$\left[\begin{bmatrix}a\\b\end{bmatrix}-\begin{bmatrix}0\\0\end{bmatrix}\right]^T * \begin{bmatrix}1\\0\end{bmatrix} = a$	
	2	1	1		1	$\begin{bmatrix}0\\0\end{bmatrix}$	(1;1)	$\left[\begin{bmatrix}0\\0\end{bmatrix}-\begin{bmatrix}a\\b\end{bmatrix}\right]^T * \begin{bmatrix}1\\1\end{bmatrix} = -a - b$	
		3			0		(1;0)	$\left[\begin{bmatrix}0\\0\end{bmatrix}-\begin{bmatrix}a\\b\end{bmatrix}\right]^T * \begin{bmatrix}1\\0\end{bmatrix} = -a$	

Note: In all cases, Group 1 (j = 1) denotes bus choice observations and Group 2 (j = g) denotes non-bus choice observations. As Eq. 28 and Eq. 29 are based on a logit membership model (Albert and Anderson, 1984), the α_g vector of the reference group g*th* (e.g., α_2 of Group 2) is set equal vector zero.

In the first two cases of data separation, because the existence of the vector α_1 is key to determining data separation, we present here two particular solutions of α_1 (e.g., α_1 = (-1; 2) in the first case of complete separation) to prove its existences noting that the number of solutions is in fact infinite. The result in Table 24 showed that these two solutions of α_1 satisfied all the conditions of complete and quasi-complete separation in Eq. 28 and Eq. 29, and hence confirming the existence of complete and quasi-complete separation in the first two cases in Figure 7. In the last case of normal overlaps, we instead use a general form of α_1 = (a; b), a and b ∈ R. The result showed that finding non-zero values for a and b that satisfy Eq. 28

(for complete separation checking) and/or Eq. 29 (for quasi-complete separation checking) for both four observations at the same time is impossible. The non-existence of α_1 in this case thus implies that the data is not being separated.

Appendix B. Estimates of parameters for latent variables of ICLV and LCC model in the case study in Chapter 4.

	ICLV		LCC	
	Estimate	t-test	Estimate	t-test
Determinants of EN				
Intercept λ0_EN	0.64	10.10	1.23	13.80
Accident_yes	0.15	2.79	0.22	2.82
Elder	0.17	2.43	0.24	2.33
Male	-0.11	-2.16	-0.15	-2.03
Measurement for EN				
EN1	1.00	N/A	0.69	11.00
EN3	0.98	9.80	0.67	10.70
EN5	1.54	12.40	1.06	14.60
EN7	1.46	11.00	1.00	N/A
EN9	1.55	11.00	1.06	12.90
EN11	1.38	11.30	0.95	13.20
EN13	1.36	11.40	0.93	13.40
EN15	1.37	11.50	0.94	13.40
Determinants of APA				
Intercept λ0_APA	0.78	12.50	0.81	12.80
Elder	0.54	5.36	0.51	4.97
High_income	0.32	4.46	0.30	4.05
Measurement for APA				
APA1	1.00	N/A	1.00	N/A
APA2	1.04	12.30	1.02	12.20
APA7	1.42	16.20	1.41	16.40
APA8	1.04	14.20	1.04	14.30
APA9	0.91	13.20	0.91	13.40
APA10	0.96	13.00	0.96	13.10

Note: N/A: Not available.

Appendix C. The estimates of the LCC model with 90% "training" sample and 85% "training" sample in the case study in Chapter 4.

	LCC model with 90% training sample		LCC model with 85% training sample	
	Estimate	t-test	Estimate	t-test
Intercepts				
BI^{C1}	-1.60	-3.59	-1.51	-3.27
$RAIL^{C1}$	-2.07	-4.08	-2.10	-4.02
WA^{C1}	-1.86	-4.87	-1.85	-4.57
BI^{C2}	-17.60	-1.28[(a)]	-16.50	-1.46[(a)]
$RAIL^{C2}$	-3.74	-3.62	-3.62	-3.53
Mode attributes				
Travel cost^{C1}	-3.75	-3.26	-3.53	-2.96
Travel time by DA^{C1}	0.06	0.051[(a)]	-0.28	-0.26[(a)]
Out-vehicle travel time by RAIL^{C1}	-3.82	-3.44	-3.85	-3.36
Travel time by BI^{C1}	-5.53	-5.38	-5.68	-5.21
Travel time by WA^{C1}	-4.89	-5.29	-5.36	-5.16
Travel cost^{C2}	-35.50	-2.72	-35.00	-2.84
Travel time by DA^{C2}	-18.10	-2.49	-17.20	-2.61
Out-vehicle travel time by RAIL^{C2}	-10.30	-1.91	-9.81	-2.01
Travel time by BI^{C2}	-17.70	-0.86[(a)]	-17.50	-0.87[(a)]
Socio-demographic characteristics				
Accident_yes_BI	-0.53	-1.64[(a)]	-0.63	-1.89
Accident_yes_RAIL	-0.55	-1.63[(a)]	-0.50	-1.46[(a)]
Company_staff_RAIL	0.36	1.04[(a)]	0.30	0.835[(a)]
High_edu_RAIL	0.82	2.14	0.61	1.54[(a)]
Male_BI	0.85	2.57	0.85	2.51
Part_time_job_RAIL	0.78	1.49[(a)]	0.69	1.27[(a)]
Company_staff_BI	-0.41	-1.21[(a)]	-0.48	-1.4[(a)]
Unemployed_BI	-0.48	-0.73[(a)]	-0.42	-0.62[(a)]
Membership allocations				
Intercept $\delta 1$	1.11	2.94	1.00	2.56
EN	-0.36	-1.69	-0.32	-1.48[(a)]
APA	0.33	1.70	0.37	1.76
Model statistics				
Number of estimated parameters:	75		75	
Number of respondents	737		697	
Number of observations	1643		1559	
Number of draws	10,000		10,000	
Final log likelihood	-12737.97		-12020.48	
Rho-squared (ρ)	0.317		0.315	
Akaike Information Criterion (AIC)	25625.95		24190.97	
Bayesian Information Criterion (BIC)	25971.14		24531.98	

Note: See the note under Table 5 for the meanings of the abbreviations.

For validating the LCC model performance, the full sample was mutually exclusively partitioned into "training" sample (e.g., including 90% and 85% respondents from the full sample) and a "validation" sample (e.g., the 10% and 15% remaining respondents, respectively). Then, the obtained estimates from the LCC model run with "training" samples were used to assess the predictability of the LCC model for the observed choices of respondents in the "validation" samples. First, we found great similarity in the estimates of LCC model with "training" samples, as shown in this appendix, and those with full sample listed in Table 5. For the effects of environmentalism and APA on the membership assignment probabilities, no noticeable differences were found in the three cases, except for the slight reductions in the t-tests arguably due to the uses of reduced samples. Next, the rho-square (ρ) index, calculated by one minus the ratio of the final log-likelihood to the initial log-likelihood (Train, 2009), was designated as the criterion for assessing the model predictability of the LCC model. In the validation analysis, the final log-likelihood of the LCC model was calculated by simulating the observed choices of the respondents in "validation" samples. The estimates of the LCC model with "training" samples shown in Appendix C were used as fixed parameters for this simulation. The initial log-likelihood was calculated in the same way but all the parameters of the LCC model were fixed equal to zero. Following this approach, the rho-squares of the LCC model for 10% "validation" sample and 15% "validation" sample were calculated at 0.264 and 0.287, respectively. Comparing to the rho-squares of the LCC model for 90% "training" sample and 85% training sample shown in this appendix at 0.317 and 0.315, respectively, the reductions in model predictability (less than 20% in percentage decreases) are acceptable.