The influences of environmentalism and attitude towards physical activity on mode choice: The new evidences.

Tran Viet YEN[a*], Toshiyuki YAMAMOTO[b], Hitomi SATO[c]

[a*] Graduate School of Engineering, Nagoya University, Nagoya, 464-8603, Japan; E-Mail: tranvietyen@gmail.com; TEL: +81-052-789-3565, Nagoya University;

[b] Institute of Materials and Systems for Sustainability, Nagoya University; E-Mail: yamamoto@civil.nagoya-u.ac.jp; TEL: +81-052-789-4636;

[c] Institutes of Innovation for Future Society, Nagoya University; E-Mail: sato@trans.civil.nagoya-u.ac.jp; TEL: +81-052-789-3565;

Declarations of interest: none

Acknowledgements

This study is funded by the Nagoya University, Japan. We would like to thank two anonymous reviewers for their helpful comments that have led to improvements in this study.

Abstract

The worldview on environmentalism has evolved significantly from traditional environmental concerns to the emergence of some new concepts, such as the limit to the human ability and the balance of nature. Transport policymakers may pose a question of whether this new way of thinking has an effect on mode choice. However, a clear answer to this question has not been found. Similarly, the intuitive expectation that physical activity can be a motivation for the selection of more physically active travel modes has not been well documented. This study attempts to investigate the potential influences of the ecological view on environmentalism and attitude towards physical activity on mode choice. The analytic data comes from a sample of 821 respondents with 1840 reported trips in an online survey conducted in Nagoya, Japan in 2018. The postulated effects were investigated in the framework of an integrated choice and latent variable model and a latent class choice model. The estimates from our models showed that environmentalism had a positive effect on the share of rail though its effect on class assignment, and attitude towards physical activity had a positive effect on both utilities and shares of bicycling and walking. In addition, findings from our study signified the importance of heterogeneity treatments in mode choice models with latent variables.

Keywords

Ecological view on environmentalism; Revised New Ecological Paradigm (NEP) Scale; Attitude towards physical activity; travel mode choice;

1. Introduction

In the discussion on the 'Psychology of Choice', McFadden (2000) described psychological factors as having 'strong and sometimes surprising impacts on perceptions and on choice behavior', and that these effects are stable in experiments. Taken together, these discussions might explain a significant literature in choice modelling with focus on psychological factors.

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 (Idris et al., 2015). Although in many cases these factors showed expected and significant impacts on mode choice, there are also some concerns regarding the issue of endogeneity. Taking attitudes as an example, Kroesen and Chorus (2018) might be the first ones to explicitly compare the pros and cons of including specific and general attitudes in travel behavior analysis. Compared with the latter ones, specific attitudes are more correlated with the travel behaviors, an expected outcome for policymakers, but at the cost of severe endogeneity. For instance, the correlation between a level of agreeing to a statement such as 'I like to travel by public transport' and the action of 'traveling by public transport' would be expected as much higher than the case of a statement such as 'I care about ecology system' and the same behavior. Nevertheless, at the same time, the specific attitudes add little information on the determinants of the behaviors than the latter case due to high endogeneity. Thus, the outcomes of mode choice models with latent variables can be more meaningful to the policy if the latent variables are more exogenous to the mode choice behaviors.

In this study, we are interested in the potential effects of environmentalism, featured by the world view of the earth as an ecology system, and attitude towards physical activity (APA) –a highly exogenous general attitude towards travel behaviors– on mode choice. Environmentalism can be considered a general attitude towards human's impacts on global environment (Fransson and Gärling, 1999) and in some sense, is related to cares for social benefits. Contrary to this, APA is connected with individual's private benefits in terms of maintaining physical health, and can be seen as a general attitude towards physical activity. The two general attitudes are increasingly apparent and dominant in modern life, nevertheless their potential effects on mode choice were not well documented. The comparison between the effects of two representatives for the two extremes of human's cares for social and personal benefits on mode choice may reveal interesting facts for both mode choice practices and policies.

First, although environmentalism is not a new topic in mode choice analysis, more studies are still needed to confirm its importance in the context of the recent global ecological issues. Previous studies on the influences of environmentalism on mode choice show inconsistent results although the main finding is its positive effects on the choices for mass transport (Bouscasse, 2018). For example, environmental preference was found to increase the likelihood of choosing train versus bus, which was considered less environmentally friendly than train (Vredin Johansson et al., 2006), men with more pro-environmental attitude are less likely to use car for commuting journey (Roberts et al., 2018), and people with positive attitude towards environment protection are more likely to choose public transport (Atasoy et al., 2013; Kim et al., 2012; Schüssler and Axhausen, 2011). 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). In addition, Dunlap (2000) signified 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[1]. He then proposed a revision to the New Environmental Paradigm (NEP) scale (Dunlap and Van Liere, 1978), or, in short, the revised NEP that captures some new facets of ecological issues, such as exemptionalism and ecocrisis. The revised NEP is

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

featured by the worldview of the globe as an ecology system. However, previous studies that consider this new conceptualization for environmentalism explicitly in a mode choice context are very limited. For these reasons, we attempt to examine the potential effects of environmentalism measured using the revised NEP on mode choice. The NEP scale is the most widely used scale for environmentalism (Stern et al., 1995) and we are interested in whether or not it can yield an effect on mode choice, such as the way that environmentalism with traditional definitions in previous studies did.

The integration of APA in mode choice, on the other hand, potentially enriches the literature and at the same time, can suggest some advices for both transport and health policymakers. First, as the number of general attitudes investigated in mode choice analysis is quite limited, we attempt to expand the range of determinants of mode utilities by considering a new form of general attitude. For transport policies, we expect to suggest that mode choice behaviors can be intervened by information campaigns aimed at raising awareness of the importance of physical activity to individual's physical health, and that transport policies can have some marginal benefits from health policies in promoting more physical activity level. In addition, this investigation may be helpful for the discussions on the social effects of education and information campaigns aimed at raising physical activity level. Today, sedentary work environment and car dependence have resulted in continuously declines in opportunities for physical activity that consequently lead to negative effects on health, sustainable development and the economy (Bull et al., 2010). Inactivity has been identified to link to a number of health problems, such as coronary heart disease (CHD), type 2 diabetes, breast and colon cancers, and shorten life expectancy (Lee et al., 2012), and the benefit of maintaining regular physical activity to the optimal health has been well acknowledged (Harris et al., 1989). Thus raising physical activity level has been recognized as a primary object of health sector (Heath et al., 2012). In this context, the additional effects on achieving healthier travel behaviors of such physical activity promotion programs, if proven, should be mentioned in the discussions regarding the potential influences of these programs. Alternatively, we expect that physical activity promotion programs are multidisciplinary, that their influences are not restricted to the health sector but can expand to transport sector. Similar to environmentalism, we found very limited studies that addressed the influences of APA on mode choice. 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, and the physical propensity was measured using only two indicators for examining desires for physically fit or sports.

To serve for these purposes, we first developed the framework for the possible effects of environmentalism and APA on non-car modes, such as public transport, cycling, and walking, which we assume to be environmentally friendly and physically active modes. A web-based survey was then conducted in Nagoya city, Japan with the questions pre-designed to capture the intended attitudes and other relevant data for our choice models. In the next section, the framework for this investigation is introduced. The data description is presented in Section 3. The analysis results are presented in Section 4, followed by the discussions and conclusions in Section 5 and 6 respectively.

2. Model framework

A common practice in examining the effects of attitudes on mode choice is to let these latent variables to directly cause mode utilities. This gave rise to extensive uses of the integrated choice and latent variable (ICLV) models (Ben-Akiva et al., 2002) in mode choice studies recently. Examples of employing ICLV models for examining the effects of general attitudes on mode choice can be found in Atasoy et al., 2013, Sottile et al., 2015b, 2015a and Vredin Johansson et al., 2006, and a good summary on the state-of-the-art ICLV models can be found in Walker and Ben-Akiva (2002). In the ICLV framework, latent variables are treated as similar to other exploratory variables, except for the fact that they are not directly observed. Similar to choice models, ICLV models are based on the assumption of a rational decision maker who seeks to maximize his/her utility in a choice situation (Ben-Akiva et al., 1999). Thus, 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. In case of environmentalism and APA, the justification for this assumption 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[2] (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).

Another way of investigating the effects of latent variables on mode choice is through latent class choice (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

[2] 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).

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 also assume that latent variables are determinants of latent class segmentations (Gopinath, 1995; Hosoda, 1999; Motoaki and Daziano, 2015; Yazdanpanah and Hosseinlou, 2016). To see the effects of environmentalism and APA on mode choice through the framework of LCC model, we assume 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 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 study. 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, lead 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 modeled, 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).

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). The Base model, ICLV model, and LCC model are shown in Figure 1. In the following, the detailed formulations and estimation process of ICLV model and LCC model are presented.

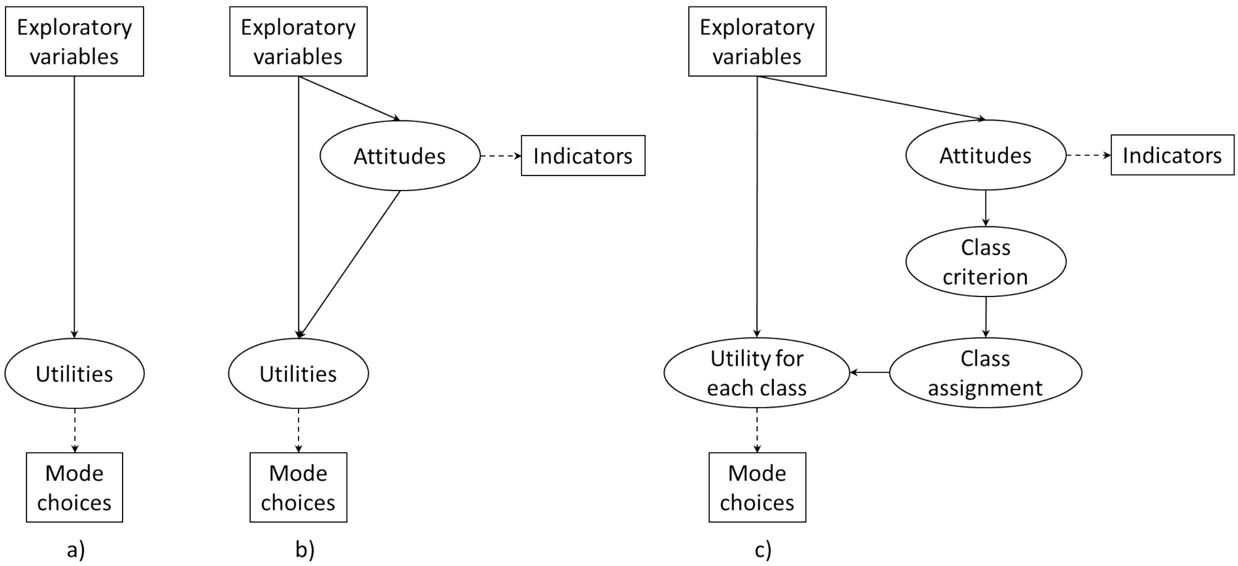

Figure 1. The Base model (a), ICLV model (b) and LCC model (c) for examining effects of environmentalism and APA on mode choice

The ICLV model formulation

Traditionally, ICVL models consist of a structural model that shows causal relationships between latent variables and their determinants, and a measurement model to relate these latent variables with their indicators.

Structural equation modelling (SEM), e.g. (Bollen, 1989), is a common technique to represent causal relations between constructs in social science. In ICLV models, SEM is used for modelling the effects of socio-demographic variables on the latent variables and between latent variables although they are not necessarily understood as true causal relations. Therefore, behavioral theories are supportive in helping ICLV models with reasonable assumptions on the structural relations among variables. Following the beginning of this section, we assume that socio-demographic characteristics cause environmentalism and APA, which in turn contribute to mode utilities. Finally, socio-demographic and mode attributes variables serve as main components of mode utilities.

The structural equations for the ICLV model are:

$$X_n^* = \lambda_0 + \lambda X_n + \omega_n \qquad (1)$$

and

$$U_{in} = \beta_0 + \beta_i X_{in} + \beta_i^* X_n^* + \xi_{in} + \varepsilon_{in} = V_{in} + \varepsilon_{in} \qquad (2)$$

where X^*_n denotes latent variables (environmentalism and APA) for the individual n; X_n represents socio-demographic characteristics of the individual n that cause his/her attitudes; ω_n is the error terms of X^*_n assumed to be normally distributed; U_{in} is the utility of mode i $\subset$ J modes viewed by the individual n; X_{in} denotes both socio-demographic characteristics of the individual n and attributes of mode i that are assumed to affect the utility of mode i; ξ_{in} is the error component of U_{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, stands for the correlation between sequence of choices of that alternative); λ, β_i and β_i^* are coefficients that represent the effects of X_n on X^*_n, X_{in} on U_{in}, and X^*_n on U_{in} respectively; λ_0 and β_0 are intercepts for X^*_n and U_{in}; V_{in} = f(X_{in}; X^*_n; ξ_{in}) is the specific part of utility of mode i; ε_{in} is the unobserved utility of mode i viewed by the individual n, assumed to be Gumbel type I distributed.

As latent variables and utilities are assumed not directly observed, a measurement model is required to identify them by relating them with manifestation variables (e.g., the psychological indicators and mode choices).

The measurement equation for the k*th* psychological indicator of the individual n is:

$$z_{kn} = \beta_{0k} + \beta_k X_n^* + \varepsilon_{kn} \qquad (3)$$

where β_k is the correlation between the k*th* indicator and the corresponding latent variable; β_{0k} is the intercept for the k*th* indicator; ε_{kn} is the error term for the k*th* indicator, assumed to be normally distributed. We designated the Likert scale with five levels (e.g., from 1 to 5) for all the attitudinal questions. For this reason, the variables for the psychological indicators will be treated as categorical with five possible discrete values (e.g., from 1 to 5). Furthermore, 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).Thus, the probability that the individual n gives the answer $l \subset L = [1 ,.., 5]$ to the question of the k*th* indicator conditioned on the distribution of the (error terms of) latent variables X^*_n is:

$$P_n(l.\,k|\,\omega_n) = P(\,\tau_{l-1} \leq z_{kn} \leq \,\tau_l) = \Phi(\,\tau_l - \beta_k X^*_n) - \Phi(\,\tau_{l-1} - \beta_k X^*_n) \qquad (4)$$

where Φ is the CDF of the normal distribution.

For the measurement of mode utility, the probability that mode i is chosen by the individual n conditioned on the distribution of the (error terms of) latent variables X^*_n and the distribution of the component representing for correlations between repeated choices ξ_{in} is:

$$P^{ICLV}_n(\,i|\,\omega_n;\,\xi_{in}) = \frac{e^{V_{in}}}{\sum_{j \subset J} e^{V_{jn}}} \qquad (5)$$

The LCC model formulation

Traditionally, LCC models include 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 modelling the class probabilities (Hess, 2014; Yazdanpanah and Hosseinlou, 2016). Applying this practice, the probability that the individual n belongs to Class 1 (relative to Class 2) conditioned on his/her attitudes X^*_n (and hence, the error terms ω_n) is given as:

$$\pi_{n,C=1}(\omega_n) = \frac{e^{\delta_1 + \tau X_n^*}}{1 + e^{\delta_1 + \tau X_n^*}} \tag{6}$$

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 attitude X^*_n on the probability of falling into Class 1 and; C=1 denotes Class 1.

As we have reversed the scores of the indicators with negative questionnaire format, 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 in Equation 6 and their indicators follows Equation 1, 3 and 4. The specific choice model for each class has the same form as in Equation 2 with the only exception that a class label is added. Thus, the utility of mode i for the individual n belonging to Class $C \subset [C1; C2]$ is,

$$U^c_{in} = \beta^c_0 + \beta^c_i X_{in} + \xi_n + \varepsilon^c_{in} = V^c_{in} + \varepsilon^c_{in} \tag{7}$$

where ξ_n denotes the correlations between repeated choices of the same person n[3], and $V^c_{in} = f(X_{in}; \xi_n)$ is the specific part of utility of mode i viewed by the person n in class C and conditioned on the value of ξ_n. The probability that mode i is chosen by the individual n, conditioned on Class C and a given value of ξ_n, is:

$$P^{LCC}_n(i | c; \xi_n) = \frac{e^{V^c_{in}}}{\sum_{j \subset J} e^{V^c_{jn}}} \tag{8}$$

Model estimation

For estimating choice models with latent variables, there are two common methods: the sequential estimation method and the simultaneous estimation method. The sequential estimation method is more common than the latter one thanks to its advantage of being

[3] Due to the complexity of the estimation for LCC model, the coefficients representing for the correlations between alternatives in repeated choices of the same person 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.

computationally efficient, although it has been acknowledged that it produces inefficient and inconsistent estimates (Ben-Akiva et al., 2002). The simultaneous estimation method is a fully unbiased and efficient estimator, but at the cost of highly computational burdens. In this study, the simultaneous estimation method was designated.

For ICLV model, the joint probability of observing both the mode choice and attitudinal answers by the person n given the distribution of stochastic components embedded in the individual probability functions is:

$$\mathcal{L}_{\mathrm{n}}^{\mathrm{ICLV}}(\omega_n;\xi_{in}) = \prod_{\mathrm{i} \subset \mathrm{J}} P_n^{ICLV}(\mathrm{i}|\omega_{\mathrm{n}};\xi_{in})^{\mathrm{di.n}} \prod_{\mathrm{k} \subset \mathrm{K}} \left[\prod_{\mathrm{l} \subset \mathrm{L}} \mathrm{P_n}(\mathrm{l.k}|\omega_{\mathrm{n}})^{\mathrm{dl.k.n}}\right] \quad (9)$$

where $P_n(i|\omega_n;\xi_{in})$ is the probability that the person n chooses alternative i conditioned on the distribution of error terms ω_n and ξ_{in}, as defined in Equation 5; $P_n(l.k|\omega_n)$ is the probability that the person n gives the answer l to the question of k*th* indicator conditioned on the distribution of error terms ω_n, as defined in Equation 4; di.n is the dummy variable that takes the value of 1 if the individual n chose alternative i and 0 otherwise; dl.kn is the dummy variable that takes the value of 1 if the individual n gave the answer l to the question of k*th* indicator and 0 otherwise. 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 the person n in the ICLV model framework:

$$\mathcal{L}_{\mathrm{n}}^{\mathrm{ICLV}} = \iint_{\omega_{\mathrm{n}},\,\xi_{\mathrm{n}}=-\infty}^{+\infty} \mathcal{L}_{\mathrm{n}}^{\mathrm{ICLV}}(\omega_{\mathrm{n}};\xi_{in})\,\mathrm{d}(\omega_{\mathrm{n}};\xi_{in}) \quad (10)$$

For LCC model, the probability that the individual n choose mode i is the average of the probabilities of his/her choices under two classes weighted by the corresponding class probabilities:

$$\mathrm{P_n^{LCC}}(\mathrm{i}|\xi_{\mathrm{n}}) = \sum_{\mathrm{c}=1}^{2} \pi_{\mathrm{n,c}} \prod_{\mathrm{i} \subset \mathrm{J}} P_n^{LCC}(\mathrm{i}|\mathrm{c};\xi_{\mathrm{n}})^{\mathrm{di.n}} \quad (11)$$

where $P_n(i|c;\xi_n)$ is the probability that the person n chooses mode i conditioned on being in class C and ξ_n; $P_n^{LCC}(i|\xi_n)$ is the probability that the person n chooses mode i conditioned on ξ_n. The joint probability of observing both mode choice and attitudinal choices of the individual n conditioned on ω_n and ξ_n is:

$$\mathcal{L}_n^{LCC}(\omega_n;\xi_n) = \prod_{i\subset J} P_n^{LCC}(i|\xi_n)^{d_{i.n}} \prod_{k\subset K}\left[\prod_{l\subset L} P_n(l.k|\omega_n)^{d_{l.k.n}}\right] = \left\{\sum_{c=1}^{2}\pi_{n,c}\prod_{i\subset J} P_n^{LCC}(i|c;\xi_n)^{d_{i.n}}\right\}\left\{\prod_{k\subset K}\left[\prod_{l\subset L} P_n(l.k|\omega_n)^{d_{l.kn}}\right]\right\}$$

(12)

Similar to the ICLV model, integrating the conditional likelihood in Equation 12 results in the unconditional probability of observing all the mode choice and attitudinal choices of the individual n under LCC model:

$$\mathcal{L}_n^{LCC} = \iint_{\omega_n,\xi_n=-\infty}^{+\infty} \mathcal{L}_n^{LCC}(\omega_n;\xi_n)\,d(\omega_n;\xi_n) \qquad (13)$$

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 this study, we set the number of draws for ω_n and ξ_{in} (in the Base model and the ICLV model) and ξ_n (in the LCC model) for approximating all the integrals at 10,000.

3. The dataset

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[4] 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.

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

[4] 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.

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[5]. 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, 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

Mode / Attribute	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				

[5] 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.

Attribute \ Mode	DA	SH	TA	MB	RAIL	BUS	BI	WA
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 problems and physical activity. The 15 original items in English of the revised NEP scale were used to measure individual's environmentalism, and 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.

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[6] 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[7] 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.

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 junior high school)	6.2 (2.2)	Hospital	3.85%
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

[6] Data separation refers to the cases where one variable, or a combination of several independent variables, perfectly or nearly perfectly predicts the dependent variable. In case of mode choice models, data separation can happen when exploratory variables can perfectly predict the mode choice probabilities.

[7] 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.

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[8]. 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[9]. 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 principle component analysis (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) and lowest ones (2.71, 2.68 and 2.65 for EN4, EN6 and EN14 respectively), it appears that *respondents in our analytic sample*

[8] This information is reachable at the city website: http://www.city.nagoya.jp/en/page/0000014169.html
[9] 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

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

		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	3.32 (0.92)			0.55	

		Mean (sd)	Factor 1	Factor 2	Factor 3	Factor 4
	with the impacts of modern industrial nations					
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 humankind has been greatly exaggerated	3.11 (0.78)			0.58	
EN11	The earth is like a spaceship with very limited room and resources	3.61 (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. Results

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 A. 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[10], we excluded WA from the choice set of the individuals in Class 2. The set of parameters for Class 2 is thus different (e.g., less than) from that of Class 1. The free package Biogeme (Bierlaire, 2016) was used for the model estimation.

Table 5. Estimates of Base model, ICLV model and LCC model.

	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)]

[10] 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 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
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 $\delta 1$					0.86	2.36
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)**: Not 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.

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[11]. While the PMS of DA in the two classes are not noticeably different (e.g., the PMS of DA in Class 1

[11] 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.

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.

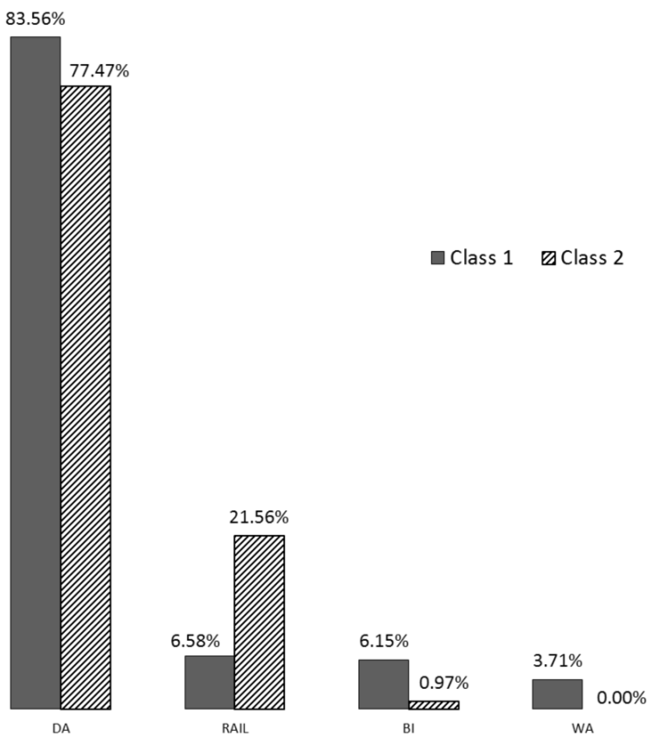

Figure 2. The predicted mode shares for two classes in the LCC model.

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 Equation 6, Equation 8, and Equation 11 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 2. 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).

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.

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.

5. Discussions

Recently, ecological crises and inactivity are receiving increasing attentions of both sociology studies and human being. These concerns may have an impact on the subsequent behaviors and that relationship may be interesting for policymakers. To test the notion that the general attitudes towards ecological crisis and towards physical activity might be reflected in the subsequent environmentally friendly behaviors and physically active behaviors respectively, we employed two formulations for the integrations of environmentalism and APA on mode choice which are different in the way these constructs are connected with mode choice. The estimation results and the supportive analyses showed evidences for the positive effects of EN and APA on mode choice. In the followings, we discuss about how to translate these findings into literature and policy significances.

First, environmentalism, as measured using the revised NEP scale, 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.

Third, 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.

Forth, regarding the estimates of parameters for mode attributes, we found only significant effect of out-vehicle travel time by RAIL on RAIL utility. This effect might contain certain amount of bias due to the bias in the self-report out-vehicle travel time by rail. This suggests that improvements in rail services that reduce this out-vehicle time, such as improving service frequency and accessibility, can encourage car drivers to choose rail for their frequent trips.

Finally, we suggest future studies to consider the effects of environmentalism and APA on mode choice models of different choice sets. The observed mode shares in both our raw data and the analytic sample 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. Another suggestion is related to the use of LCC model. The differences in car drivers' sensitivities for travel times between modes have been made much clearer in the latent class framework. This signifies the importance of treatments for individual heterogeneities in mode choice.

6. Conclusions

In this study, we investigated how environmentalism, as measured using the revised NEP scale, and APA play a role in mode choice. We found a positive influence of environmentalism on mode share of rail and a positive influence of APA on mode utilities and mode shares of bicycle and walking. In addition, the latent class framework was useful in unraveling the effect of environmentalism on mode choice that is frequently reported as insignificant in previous studies. Finally, our study suggests about an idea of combining transport and health policies though the factor APA.

Appendix A. Estimates of parameters for latent variables of ICLV and LCC model.

	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 B. The estimates of the LCC model with 90% “training” sample and 85% “training” sample (see the note under Table 5 for the meanings of the abbreviations).

	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

	LCC model with 90% training sample		LCC model with 85% training sample	
	Estimate	t-test	Estimate	t-test
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: 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 the Appendix B, 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 B 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 Appendix B at 0.317 and 0.315, respectively, the reductions in model predictability (less than 20% in percentage decreases) are acceptable.

References

Atasoy, B., Glerum, A., Bierlaire, M., 2013. Attitudes towards mode choice in Switzerland. disP - Plan. Rev. 49, 101–117. https://doi.org/10.1080/02513625.2013.827518

Bamberg, S., 2003. How does environmental concern influence specific environmentally related behaviors? A new answer to an old question. J. Environ. Psychol. 23, 21–32. https://doi.org/10.1016/S0272-4944(02)00078-6

Ben-Akiva, M., McFadden, D., Gärling, T., Gopinath, D., Walker, J.L., Bolduc, D., Börsch-Supan, A., Delquié, P., Larichev, O., Morikawa, T., Polydoropoulou, A., Rao, V., 1999. Extended framework for modeling choice behavior. Mark. Lett. 10, 187–203. https://doi.org/10.1023/A:1008046730291

Ben-Akiva, M., Walker, J.L., Bernardino, A.T., Gopinath, D., Morikawa, T., Polydoropoulou, A., 2002. Integration of choice and latent variable models. Perpetual motion Travel Behav. Res. Oppor. Appl. challenges 431–470.

Bierlaire, M., 2016. PythonBiogeme: a short introduction, TRANSP-OR 160706 ,Series on Biogeme.

Bierlaire, M., 2015. Monte-Carlo integration with PythonBiogeme.

Bolduc, D., Boucher, N., Alvarez-Daziano, R., 2008. Hybrid choice modeling of new technologies for car choice in Canada. Transp. Res. Rec. J. Transp. Res. Board 2082, 63–71.

https://doi.org/10.3141/2082-08

Bollen, K.A., 1989. Structural equations with latent variables. Wiley.

Bouscasse, H., 2018. Integrated choice and latent variable models: A literature review on mode choice. Work. Pap.

Bull, F.., Gauvin, L., Bauman, A., Shilton, T., Kohl, H.W., Salmon, A., 2010. The Toronto Charter for Physical Activity: a global call for action. J. Phys. Act. Health 7, 421–422.

Bull, S.B., Lewinger, J.P., Lee, S.S.F., 2007. Confidence intervals for multinomial logistic regression in sparse data. Stat. Med. 26, 903–918. https://doi.org/10.1002/sim.2518

Dunlap, R.E., Van Liere, K.D., 1978. The "New Environmental Paradigm." J. Environ. Educ. 9, 10–19. https://doi.org/10.1080/00958964.1978.10801875

Dunlap, R.E., Van Liere, K.D., Mertig, A.G., Jones, R.E., 2000. Measuring endorsement of the new ecological paradigm: a revised NEP scale. J. Soc. Issues 56, 425–442. https://doi.org/10.1111/0022-4537.00176

Edwards, A., 1957. The social desirability variable in personality assessment and research. Dryden Press, New York.

Eriksson, L., 2008. Pro-environmental travel behavior : the importance of attitudinal factors, habits, and transport policy measures. Unpublished PhD Dissertation. Umeå University.

Fransson, N., Gärling, T., 1999. Environmental concern: conceptual definitions, measurement methods, and research findings. J. Environ. Psychol. 19, 369–382. https://doi.org/10.1006/JEVP.1999.0141

Frischknecht, B.D., Eckert, C., Geweke, J., Louviere, J.J., 2014. A simple method for estimating preference parameters for individuals. Int. J. Res. Mark. 31, 35–48.

https://doi.org/10.1016/J.IJRESMAR.2013.07.005

Gopinath, D., 1995. Modeling Heterogeneity in Discrete Choice Processes: Application to Travel Demand. Massachusetts Institute of Technology.

Greene, W.H., Hensher, D.A., 2013. Revealing additional dimensions of preference heterogeneity in a latent class mixed multinomial logit model. Appl. Econ. 45, 1897–1902. https://doi.org/10.1080/00036846.2011.650325

Gupta, S., Chintagunta, P.K., 1994. On using demographic variables to determine segment membership in logit mixture models. J. Mark. Res. 31, 128–136. https://doi.org/10.2307/3151952

Harris, S.S., Caspersen, C.J., DeFriese, G.H., Estes, E.H., 1989. Physical activity counseling for healthy adults as a primary preventive intervention in the clinical setting: report for the U.S. Preventive Services Task Force. JAMA 261, 3588. https://doi.org/10.1001/jama.1989.03420240102035

Heath, G.W., Parra, D.C., Sarmiento, O.L., Andersen, L.B., Owen, N., Goenka, S., Montes, F., Brownson, R.C., Lancet Physical Activity Series Working Group, 2012. Evidence-based intervention in physical activity: lessons from around the world. Lancet (London, England) 380, 272–81. https://doi.org/10.1016/S0140-6736(12)60816-2

Hess, S., 2014. Latent class structures: taste heterogeneity and beyond, in: Handbook of Choice Modelling. Edward Elgar Publishing, pp. 311–330.

Hess, S., Ben-Akiva, M., GOPINATH, D., Walker, J.L., 2011. Advantages of latent class models over continuous mixture models in capturing heterogeneity. Association for European Transport.

Hess, S., Shires, J., Jopson, A., 2013. Accommodating underlying pro-environmental attitudes in a rail travel context: Application of a latent variable latent class specification. Transp. Res. Part

D Transp. Environ. 25, 42–48. https://doi.org/10.1016/J.TRD.2013.07.003

Hess, S., Train, K.., Polak, J.., 2006. On the use of a Modified Latin Hypercube Sampling (MLHS) approach in the estimation of a Mixed Logit model for vehicle choice. Transp. Res. Part B Methodol. 40 (2), 147–163. https://doi.org/10.1016/j.trb.2004.10.005

Hosoda, T. 1965-, 1999. Incorporating unobservable heterogeneity in discrete choice model : mode choice model for shopping trips.

Hurtubia, R., Nguyen, M.H., Glerum, A., Bierlaire, M., 2014. Integrating psychometric indicators in latent class choice models. Transp. Res. Part A Policy Pract. 64, 135–146. https://doi.org/10.1016/J.TRA.2014.03.010

Idris, A.O., Nurul Habib, K.M., Shalaby, A., 2015. An investigation on the performances of mode shift models in transit ridership forecasting. Transp. Res. Part A Policy Pract. 78, 551–565. https://doi.org/10.1016/J.TRA.2015.06.012

Kamakura, W.A., Russell, G.J., 1989. A probabilistic choice model for market segmentation and elasticity structure. J. Mark. Res. 26, 379. https://doi.org/10.2307/3172759

Kamargianni, M., Dubey, S., Polydoropoulou, A., Bhat, C.R., 2015. Investigating the subjective and objective factors influencing teenagers' school travel mode choice – An integrated choice and latent variable model. Transp. Res. Part A Policy Pract. 78, 473–488. https://doi.org/10.1016/J.TRA.2015.06.011

Kim, J.H., Bae, Y.K., Chung, J.-H., 2012. Effects of personal proenvironmental attitudes on mode choice behavior: New ecofriendly water transit system in Seoul, South Korea. Transp. Res. Rec. 2274, 175–183. https://doi.org/10.3141/2274-19

Kroesen, M., Chorus, C., 2018. The role of general and specific attitudes in predicting travel behavior – A fatal dilemma? Travel Behav. Soc. 10, 33–41.

https://doi.org/10.1016/J.TBS.2017.09.004

Lee, I.-M., Shiroma, E.J., Lobelo, F., Puska, P., Blair, S.N., Katzmarzyk, P.T., Lancet Physical Activity Series Working Group, 2012. Effect of physical inactivity on major non-communicable diseases worldwide: an analysis of burden of disease and life expectancy. Lancet (London, England) 380, 219–29. https://doi.org/10.1016/S0140-6736(12)61031-9

Likert, R., 1932. A technique for the measurement of attitudes. New York : The Science Press.

Maloney, M.P., Ward, M.P., 1973. Ecology: Let's hear from the people: An objective scale for the measurement of ecological attitudes and knowledge. Am. Psychol. 28, 583–586. https://doi.org/10.1037/h0034936

McFadden, D., 2001. Disaggregate behavioral travel demand's RUM side—a 30 years retrospective, in: Hensher, D.A. (Ed.), Travel Behavior Research. Elsevier, Amsterdam, pp. 17–63.

Morikawa, T., Ben-Akiva, M., McFadden, D., 2002. Discrete choice models incorporating revealed preferences and psychometric data. Econom. Model. Mark. 16, 29–55. https://doi.org/10.1016/S0731-9053(02)16003-8

Motoaki, Y., Daziano, R.A., 2015. A hybrid-choice latent-class model for the analysis of the effects of weather on cycling demand. Transp. Res. Part A Policy Pract. 75, 217–230. https://doi.org/10.1016/J.TRA.2015.03.017

Nederhof, A.J., 1985. Methods of coping with social desirability bias: a review. Eur. J. Soc. Psychol. 15, 263–280.

Parry, H.J., Crossley, H.M., 1950. Validity of responses to survey questions. Public Opin. Q. 14, 61. https://doi.org/10.1086/266150

Paulhus, D.L., 1984. Two-component models of socially desirable responding. J. Pers. Soc. Psychol.

46, 598–609. https://doi.org/10.1037/0022-3514.46.3.598

Paulssen, M., Temme, D., Vij, A., Walker, J.L., 2014. Values, attitudes and travel behavior: a hierarchical latent variable mixed logit model of travel mode choice. Transportation (Amst). 41, 873–888. https://doi.org/10.1007/s11116-013-9504-3

Politis, I., Papaioannou, P., Basbas, S., 2012. Integrated choice and latent variable models for evaluating flexible transport mode choice. Res. Transp. Bus. Manag. 3, 24–38. https://doi.org/10.1016/J.RTBM.2012.06.007

Poortinga, W., Steg, L., Vlek, C., 2004. Values, environmental concern and environmental behavior: a study into household energy use. Environ. Behav. 36, 70–93. https://doi.org/10.1177/0013916503251466

Roberts, J., Popli, G., Harris, R.J., 2018. Do environmental concerns affect commuting choices?: hybrid choice modelling with household survey data. J. R. Stat. Soc. Ser. A (Statistics Soc. 181, 299–320. https://doi.org/10.1111/rssa.12274

Schüssler, N., Axhausen, K.W., 2011. Psychometric scales for risk propensity, environmentalism and and variety seeking. Arbeitsberichte Verkehrs- und Raumplan. 725. https://doi.org/10.3929/ETHZ-A-006689653

Sottile, E., Cherchi, E., Meloni, I., 2015a. Measuring soft measures within a stated preference survey: the effect of pollution and traffic stress on mode choice. Transp. Res. Procedia 11, 434–451. https://doi.org/10.1016/J.TRPRO.2015.12.036

Sottile, E., Meloni, I., Cherchi, E., 2015b. A hybrid discrete choice model to assess the effect of awareness and attitude towards environmentally friendly travel modes. Transp. Res. Procedia 5, 44–55. https://doi.org/10.1016/J.TRPRO.2015.01.017

Steg, L., Vlek, C., 2009. Encouraging pro-environmental behaviour: An integrative review and research agenda. J. Environ. Psychol. 29, 309–317. https://doi.org/10.1016/J.JENVP.2008.10.004

Stern, P.C., 2000. Toward a coherent theory of environmentally significant behaviour., Journal of Social Issues.

Stern, P.C., Kalof, L., Dietz, T., Guagnano, G.A., 1995. Values, beliefs, and proenvironmental action: attitude formation toward emergent attitude objects. J. Appl. Soc. Psychol. 25, 1611–1636. https://doi.org/10.1111/j.1559-1816.1995.tb02636.x

Temme, D., Paulssen, M., Dannewald, T., 2007. Integrating latent variables in discrete choice models – How higher-order values and attitudes determine consumer choice.

Train, K., 2009. Discrete choice methods with simulation. Cambridge University Press.

Van Exel, N.J.A., Rietveld, P., 2009. Could you also have made this trip by another mode? An investigation of perceived travel possibilities of car and train travellers on the main travel corridors to the city of Amsterdam, The Netherlands. Transp. Res. Part A Policy Pract. 43, 374–385. https://doi.org/10.1016/j.tra.2008.11.004

Vredin Johansson, M., Heldt, T., Johansson, P., 2006. The effects of attitudes and personality traits on mode choice. Transp. Res. Part A Policy Pract. 40, 507–525. https://doi.org/10.1016/J.TRA.2005.09.001

Walker, J.L., Ben-Akiva, M., 2002. Generalized random utility model, Mathematical Social Sciences.

Walker, J.L., Li, J., 2007. Latent lifestyle preferences and household location decisions. J. Geogr. Syst. 9, 77–101. https://doi.org/10.1007/s10109-006-0030-0

Yáñez, M.F., Raveau, S., Ortúzar, J. de D., 2010. Inclusion of latent variables in Mixed Logit models: Modelling and forecasting. Transp. Res. Part A Policy Pract. 44, 744–753.

https://doi.org/10.1016/J.TRA.2010.07.007

Yazdanpanah, M., Hosseinlou, M.H., 2016. The influence of personality traits on airport public transport access mode choice: A hybrid latent class choice modeling approach. J. Air Transp. Manag. 55, 147–163. https://doi.org/10.1016/J.JAIRTRAMAN.2016.04.010