CHAPTER 10

An empirical assessment of the impact of incorporating attitudinal variables on model transferability

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Abstract

This chapter focuses on assessing the benefits of incorporating attitudinal and perception variables for the spatial transferability of travel forecasting models. Specifically, this study compares the spatial transferability, in an empirical setting, for three model structures: 1) multinomial logit (MNL), 2) integrated choice and latent variable (ICLV) models and 3) MNL with factor scores. Transferability is assessed by applying the models estimated in one spatial context to another spatial context. The data utilized for assessing the spatial transferability in the three contexts comes from a survey conducted among 1148 respondents across the United States – primarily the Midwest and Southeast. In the survey, respondents were asked about their preferred intended use of autonomous vehicles, along with personal and household characteristics, current travel characteristics, and perceptions about benefits and concerns related to autonomous vehicles. The study found that the ICLV models estimated had similar transferability to fixed coefficient MNL models with no improvement in transferability observed. But it was found that additional information that could lead to improvement of transferability was found when factor scores were directly incorporated into a MNL model. The chapter concludes with a discussion of possible transferability implications for ICLV model use.

Keywords:

Integrated Choice and Latent Variable Model, Hybrid Choice Model, Factor Analysis, Psychometric Indicators

1. Introduction

Spatial transferability of travel demand forecasting models, i.e. the ability to use a travel demand forecasting model developed in one region for travel demand forecasting in another region, is of considerable interest [1, 2, 3]. The ability to transfer models between regions can save significant cost and time – particularly for regions that cannot afford to build a model from scratch. The issue of spatial transferability is relevant to not just small/mid-sized regions in developed countries, who are generally short of funds to conduct an extensive data-collection. But it is also relevant to planning agencies in many developing countries, which generally have a meager budget for transportation planning [4].

Ben-Akiva [5] and Hansen [6] suggested four different levels at which transferability (spatial, temporal or cross-cultural) must be considered from a theoretical standpoint: 1) *underlying theory of travel behavior*, which involves transferability of broad behavioral postulates, such as the random utility maximization decision rule; 2) *model structure*, which involves transferability of mathematical model structure, such as logit, nested logit, mixed logit and probit models of discrete choice; 3) *empirical specification*, which involves transferability of explanatory variables in the model specification; and 4) *parameter values*, which involves transferability of parameter estimates across contexts. Ideally, a forecasting model is considered perfectly transferable between contexts if the model is transferable from the above mentioned four standpoints. However, perfect transferability is an unreasonable expectation due to a variety of reasons. First, there is increasing evidence of violations of *homo economicus* human behavior whereas most travel choice models in practice assume rational behavior. Not accounting for deviations from rational behavior might make these models less transferable. Second, choice of a model structure from a variety of plausible ones can also introduce approximations and reduce transferability. Third, variations in model specifications – including omission of certain explanatory variables, neglecting observed and unobserved heterogeneity, and sampling and measurement errors – can also amplify the issue and make it harder to achieve perfect transferability. Lerman [7] pointed out that as models are only abstractions of reality, the expectation of perfect transferability is too overly restrictive, and a reasonable expectation would be whether models from different contexts are close enough to being substitutable for some pre-defined purpose. Further, Koppelman and Wilmot [8] pointed out that transferability should not be viewed as a dichotomous property. Rather, transferability assessment should talk about degree of transferability. This degree of transferability can be measured in various ways and one possible method is to use the locally estimated model as a yardstick against which a transferred model is assessed. For practical purposes, if a transferred model performs nearly as good as a model estimated using locally available data (using some objective metrics of model performance), then the transferred model can be used at the local context.

Over the years, researchers have argued that a positive relationship exists between model specification and model transferability [1, 7, 8, 9]. The hypothesis is that since transferability is based on the assumption of behavioral regularity across contexts, well specified models should be able to capture this behavioral regularity better than naïve models and hence are expected to be more transferable [8]. In this context, it has been speculated that inclusion of so-called "soft factors" (or latent variables)—attitudes, perception, norms, and beliefs—which greatly influence an individual's decisions, might produce models with better transferability than traditionally specified models with only observable socio-economic characteristics [10].

This study is aimed at empirically testing the hypothesis that travel demand forecasting models with observable as well as latent variables are more transferable than traditionally estimated models with just observable explanatory variables. Specifically, we compare the spatial transferability of traditionally estimated multinomial logit (MNL) models with the spatial transferability of integrated choice and latent variable (ICLV) models, which are the most common approach to incorporate latent variables in discrete choice models. ICLV models can offer greater insights into the decision-making process by including additional information through measurement equations for the latent variables. It is also believed that ICLV models produces more efficient model outputs (i.e. with less variation) such as demand elasticities and market predictions [11]. Further, although existing work has examined whether ICLV models are more behaviorally sound, the spatial transferability of ICLV models has not been fully explored. It may be hypothesized that well-specified ICLV models – particularly, ones that better capture observed and unobserved heterogeneity in the data – will offer better spatial transferability than traditional MNL models that are widely used in practice. One may speculate that this will be due to how ICLV models produce non-linearity in the impact of exogenous variables on the choice outcome. However, there is little empirical evidence to support or contest this hypothesis.

To test the above-mentioned hypothesis, this paper conducts an empirical transferability assessment using data from a survey on autonomous vehicle (AV) intended usage and attitudes. The available data is used to model individuals' intention to use AVs, when they become available, using traditionally estimated MNL models (without any latent variables) and ICLV models. Then, a spatial transferability assessment is performed using various assessment techniques and metrics available in the literature.

The remainder of the chapter is structured as follows. Section 2 describes the econometric model structures, transferability assessment techniques, and transferability assessment metrics used in this study. Section 3 describes the empirical setting in this study and details of the estimated models. Section 4 present the transferability assessment procedure and results. Finally, section 5 summarizes and concludes the study.

2. Econometric Models and Transferability Assessment Techniques

In the forthcoming empirical analysis, we study the spatial transferability of two econometric model structures: (1) multinomial logit and (2) integrated choice and latent variable models. This section describes these two model structures in detail and the transferability assessment technique and measures.

2.1 Multinomial Logit (MNL) Model

One of the most popular econometric model structures for modeling discrete choice outcomes is the multinomial logit (MNL) model. Its popularity is largely due to its closed form choice outcome probability expression and easy interpretability [12]. Consistent with random utility maximization theory, the multinomial logit model can be represented by a structural equation of an alternative's utility and a measurement equation relating utility maximization to the chosen alternative. The MNL model (without alternative-specific independent variables) is presented as follows:

$$U_n = Bx_n + \varepsilon_n \tag{1}$$

$$y_{nj} = \begin{cases} 1, & \text{if } U_{nj} > U_{nj'} \; \forall j' \in \{1, \dots, \dots, \dots J\} \\ 0, & \text{otherwise} \end{cases} \tag{2}$$

where U_n is a $(J \times 1)$ vector of utilities of each of J alternatives, as perceived by decision maker n; x_n is the $(K \times 1)$ vector of observable explanatory variables; B is a $(J \times K)$ matrix of model parameters denoting sensitivities to the observable variables; ε_n is the $(J \times 1)$ vector denoting the random component of the utility specification, which is assumed to be independent and identically distributed (IID) extreme value; and y_{nj} is the choice indicator, equal to one if decision-maker n chose alternative j and zero otherwise.

The probability that a decision maker n chooses alternative j has the following functional form:

$$P\left(y_{nj} = 1 \middle| x_n; B\right) = \frac{exp(\beta_j x_n)}{\sum_{j'=1}^{J} exp(\beta_{j'} x_n)} \tag{3}$$

where β_j is a $(1 \times K)$ vector corresponding to the j^{th} row of B. Equation 3 may be combined over all alternatives to yield the following probability of observing the vector of choices y_n for decision maker n:

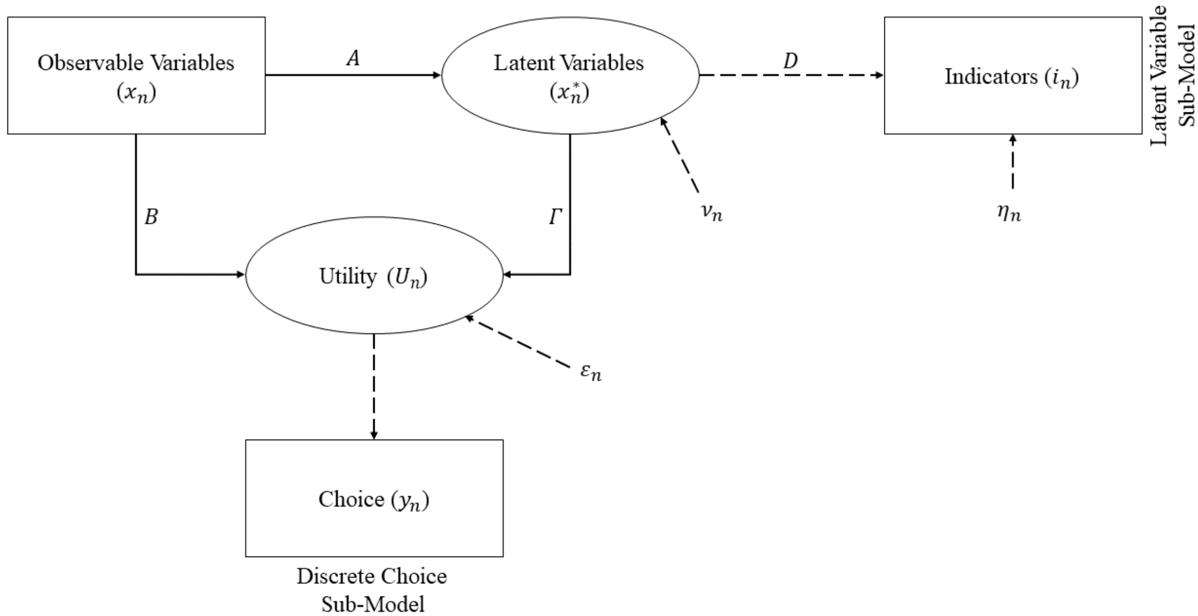
$$f_y(y_n|x_n; B) = \prod_{j'=1}^{J} [P\left(y_{nj'} = 1 \middle| x_n; B\right)]^{y_{nj'}} \tag{4}$$

The parameter estimation in the multinomial logit model is done using maximum likelihood estimation of Equation 4.

2.2 Integrated Choice and Latent Variable (ICLV) Model

Increasing emphasis on incorporating psychological factors (e.g. attitudes, norms, perception, and beliefs) into discrete choice models led to the development of integrated choice and latent variable models. The idea was that incorporation of these psychological factors would lead to a more behaviorally realistic representation of choice processes and that such models would have better explanatory power than traditional models without latent variables. Seminal papers on ICLV models by McFadden [13], Train et al. [14], Ashok et al. [15], and Ben-Akiva et al. [16] popularized this model structure among members of the travel behavior research community. Further, recent papers by Vij and Walker [11], Bolduc et al. [17], Daly et al. [18], Bhat and Dubey [19], as well as Chorus and Kroesen [20] have explored the benefits and limitations of ICLV models.

*** Insert Figure 10.1 ***



Caption: Integrated Choice and Latent Variable Framework [11]

Credit: The chapter authors

Figure 1 illustrates the ICLV model framework, which consists of two sub-components: a multinomial discrete choice model and a latent variable model. Each sub-component consists of a structural and measurement equation. Mathematically, the ICLV model (without alternative-specific independent variables) is expressed using following four equations:

$$U_n = Bx_n + \Gamma x_n^* + \varepsilon_n \tag{5}$$

$$x_n^* = Ax_n + \nu_n \tag{6}$$

$$i_n = Dx_n^* + \eta_n \tag{7}$$

$$y_{nj} = \begin{cases} 1, & \text{if } U_{nj} > U_{nj'}\ \forall j' \in \{1, \dots, \dots, \dots J\} \\ 0, & \text{otherwise} \end{cases} \tag{8}$$

where U_n is a $(J \times 1)$ vector of utilities of each of J alternatives, as perceived by decision maker n; x_n is the $(K \times 1)$ vector of observable explanatory variables; x_n^* is the $(M \times 1)$ vector of latent explanatory variables; B and Γ are the $(J \times K)$ and $(J \times M)$ matrices of model parameters denoting sensitivities to the observable and latent variables, respectively; ε_n is the $(J \times 1)$ vector denoting the random component of the utility specification; A is the $(M \times K)$ matrix of model parameters denoting the structural relationship between the latent and observable variables; v_n is the $(M \times 1)$ vector denoting the random component of that relationship; i_n is the $(R \times 1)$ vector of indicators used to measure the latent variables, assumed to represent deviations from the mean; D is the $(R \times M)$ matrix of model parameters denoting the sensitivities of the measurement equation; η_n is the $(R \times 1)$ vector denoting the random component of the measurement equation; and y_{nj} is the choice indicator, equal to one if decision-maker n chose alternative j, zero otherwise. The random components ε_n, v_n, and η_n are assumed to be mutually independent.

The most popular form of the ICLV model in the literature is the *logit kernel*, where ε_{nj} is IID gumbel across alternatives and decision makers with location parameter zero and scale parameter one. Conditional on the latent variable, the probability that a decision-maker n chooses alternative j has the following functional form:

$$P\left(y_{nj} = 1 \middle| x_n, x_n^*; B, \Gamma\right) = \frac{exp(\beta_j x_n + \gamma_j x_n^*)}{\sum_{j'=1}^{J} exp(\beta_{j'} x_n + \gamma_{j'} x_n^*)} \tag{9}$$

where β_j and γ_j are $(1 \times K)$ and $(1 \times M)$ vectors corresponding to the j^{th} row of B and Γ, respectively. Equation 9 may be combined over all alternatives to yield following conditional probability of observing the vector of choices y_n for decision maker n:

$$f_y(y_n | x_n, x_n^*; B, \Gamma) = \prod_{j'=1}^{J} \left[P\left(y_{nj'} = 1 \middle| x_n, x_n^*; B, \Gamma\right)\right]^{y_{nj'}} \tag{10}$$

With regards to the measurement indicators, in this study, we assumed that the indicators represent Likert-scale type ordered response variable as in Daly et al. [18]. In the ordered representation of the indicators, the latent variable measurement equation $(i_n = Dx_n^* + \eta_n)$ is assumed to be a propensity function driving choice of ordered response from L possible outcomes for each indicator. Assuming that η_n is independently (need not be identically) distributed normally across R indicators and N decision makers, the probability of the decision-maker n choosing ordered choice outcome l in the r^{th} measurement equation is written as:

$$P(w_{nrl} = 1 | x_n, x_n^*; D, S) = \Phi\left[\frac{\psi_l^r - \delta_r x_n^*}{s_r}\right] - \Phi\left[\frac{\psi_{l-1}^r - \delta_r x_n^*}{s_r}\right] \tag{11}$$

where w_{nrl} is the ordered choice indicator, which is equal to one if the decision maker n chooses l^{th} ordered outcome for the r^{th} indicator; $\Phi[\cdot]$ is the cumulative distribution function of standard normal distribution; ψ_l^r is the l^{th} threshold dividing the propensity function for the r^{th}

indicator; and S is the $(R \times 1)$ vector of scale parameters of η_n with s_r as the r^{th} element of S. Equation 11 can also be combined over L ordered outcomes and R indicators to yield the following probability distribution function:

$$f_w(w_n|x_n x_n^*; D, S) = \prod_{r=1}^{R} \prod_{l=1}^{L} [P(w_{nrl} = 1|x_n, x_n^*; D, S)]^{w_{nrl}} \tag{12}$$

With regards to the structural equation, the latent variables are represented using a linear-in-parameter formulation, where v_n is assumed to be distributed normally with a mean vector of zeros and covariance matrix Ω. The probability distribution associated with latent variables is expressed as:

$$f_{x_n^*}(x_n^*|x_n; A, \Omega) = (2\pi)^{-\frac{M}{2}}|\Omega|^{-\frac{1}{2}} exp(-\frac{1}{2}(x_n^* - Ax_n)^T \Omega^{-1}(x_n^* - Ax_n)) \tag{13}$$

The joint unconditional probability distribution function for the choice and measurement indicators is written as:

$$f_{y,w}(y_n, w_n|x_n, x_n^*; B, \Gamma, D, S, A, \Omega) =$$

$$\int_{x_n^*} f_y(y_n|x_n, x_n^*; B, \Gamma) f_w(w_n|x_n x_n^*; D, S) f_{x_n^*}(x_n^*|x_n; A, \Omega) dx_n^* \tag{14}$$

The unknown parameters in equation 14 are estimated using maximum simulated likelihood estimation.

Three important points need to be noted here. First, as standard practice in ordered response models, $\psi_0^r = -\infty$ and $\psi_{L+1}^r = \infty$. Second, for identification reasons, all elements of S were fixed to one. Third, again for identification reasons, the on-diagonal and off diagonal elements of Ω were fixed to one and zero respectively.

2.2.1 How are ICLV models used for forecasting?

It can be considered that in the ICLV model, the measurement equation is only an auxiliary in the estimation of the structural equation. Typically, the measurement equation is not used for forecasting purposes[1]. From a forecasting standpoint, as we are normally interested in changes in the utility functions and their repercussion on choice probabilities, any changes in the observable explanatory variables will induce changes in the latent variables, and these updated latent variables can be used to calculate updated choice probability. When forecasting, the choice

[1] If the measurement equation was required for forecasting from the choice model, it would require the analyst to first generate forecasts for the indicators. But forecasted future values for indicators are generally not available.

model probabilities in an ICLV model are calculated by marginalizing Equation 10 over the distribution of latent variable x_n^* and is written as:

$$f_y(y_n|x_n, x_n^*; B, \Gamma, A, \Omega) = \int_{x_n^*} f_y(y_n|x_n, x_n^*; B, \Gamma) f_{x_n^*}(x_n^*|x_n; A, \Omega) dx_n^* \quad (15)$$

2.3 Multinomial Logit (MNL) Model with Factors

An ICLV model uses psychometric data indirectly through the latent variable measurement model but the latent variable structural model uses no new information directly (i.e. uses only the sociodemographic variables). Thus, the ICLV produces a distribution of latent variable values based on sociodemographic, non-attitudinal data; it essentially tries to forecast the latent variable. For comparison purposes, a direct incorporation of psychometric data was performed. In this way, it is expected that this represents a theoretical limit on the level of additional information and predictive power available through the psychometric indicators. Instead of incorporating the latent factors indirectly into the choice model through the latent variables (as in ICLV models), this model directly uses an aggregate measure of latent factors in the choice model. The aggregate measure is obtained by condensing all the indicators used in this study using the principal component analysis (PCA) method.

The aggregate measure is then obtained by multiplying weights from the PCA with their corresponding indicator responses. That is, $F_n = \Phi i_n$, where F_n is an aggregate measure for indicators, Φ is a $(1 \times R)$ vector of weights and i_n is the $(R \times 1)$ vector of indicators. The calculated weight is then used as an explanatory variable in the MNL model as shown below:

$$U_n = Bx_n + \Upsilon F_n + \varepsilon_n \quad (16)$$

where U_n is a $(J \times 1)$ vector of utilities of each of J alternatives, as perceived by decision maker n, x_n is the $(K \times 1)$ vector of observable explanatory variables, B is a $(J \times K)$ matrix of model parameters denoting sensitivities to the observable variables, Υ is a $(J \times 1)$ vector of model parameters for the aggregate measure, ε_n is the $(J \times 1)$ vector denoting the random component of the utility specification, which is independent and identically distributed (IID) extreme value. The rest of the estimation procedure is same as discussed in section 2.1.

2.4 Transferability Assessment Techniques

There are two popular approaches to assess spatial transferability of travel demand forecasting models: (a) the application-based approach, and (b) the estimation-based approach.

In the application-based approach, model parameters are estimated using data from one region (the base context) and applied to data in another region (the application context) to assess how well the model in the base context predicts in the application context. This approach tests the transferability of a model as a whole, without allowing an examination of which specific parameters are transferable. In the estimation-based approach, also known as joint-context estimation, data from the base and application contexts are combined to estimate a single model while recognizing potential differences between the two contexts. This is done by estimating context specific difference parameters. Simple t-tests on these difference parameters can shed light on whether the parameter estimates are different between the two contexts. An advantage of this approach is that one can test whether each (and every) parameter in a model is transferable. The predominantly used application-based approach is used in this study to examine the transferability of MNL and ICLV models.

2.5 Transferability Assessment Metrics

Assessment metrics can be classified into absolute and relative metrics, where absolute metrics assess how well the transferred model represents the observed behavior in the application context and relative metrics assess the performance of transferred model relative to the application context model. A detailed review of various metrics available in the literature to assess spatial transferability can be found in Sikder et al. [3]. Relative Aggregate Transfer Error (RATE) metric is used in this study for the transferability assessment which is a relative metric comparing the aggregate level prediction capabilities of the base and application context models. Let *a* and *b* represent the indices for the estimated and transferred models in the study region, respectively. Similarly, PS_k and OS_k represent the predicted and observed shares for the choice alternative *k*. The relative error measure for each alternative (REM_k) is defined by $\frac{PS_k - OS_k}{OS_k}$ and the root mean square error for a model (β) applied to a dataset *m* is represented by $RMSE_m(\beta)$ and defined by $(\frac{\sum_k PS_k \times REM_k^2}{\sum_k PS_k})^{1/2}$. Finally, the RATE measure is the ratio of RMSE values of the transferred model (β_b) and the estimated model (β_a) in a region, i.e. $\frac{RMSE_i(\beta_b)}{RMSE_i(\beta_a)}$. It is important to note here that the constants of transferring model are adjusted using the procedure demonstrated by Train [12] before calculating predicted shares in the study region.

3. Study setting

In this study, we make use of data collected from a survey conducted among 1146 respondents from the United States (see Menon et al. [21] for details on the data). Respondents were asked about their preferred way of using autonomous vehicles (AVs), when they become readily available. Available options for the respondent to choose included:

- C1. Own AVs and use them only for personal use or use by family members
- C2. Own an AV and earn extra income on the side by making it available to other drivers when not needed
- C3. Own an AV and earn extra income on the side by providing rides for fellow passengers when you use it
- C4. Rent an AV as the need arises
- C5. Use AVs in the form of transportation (taxi, or public transit) provided by a service provider
- C6. Neither interested in investing in an AV nor using AVs as a transportation service.

Due to inadequate number of responses for some choices, they were grouped into three choice alternatives, namely, owning an AV (C1+C2+C3), using it as a shared vehicle (C4+C5) and not using an AV at all (C6). Apart from the response on preferred way of using an AV, the survey collected information on personal and household demographics, current travel behavior, perceptions of various attributes of AV technologies, familiarity with the technology, and perceptions of the benefits and concerns with AVs. For the transferability assessment, the total data is divided to two pairs: Florida and non-Florida, Michigan and non-Michigan. Table 1 presents a comparison of demographic characteristics between different regions, which points to a number of similarities and differences between the two regions. For example, the mean of the age of the respondents in the four datasets is around the same. Also, the number of female respondents in the Michigan dataset seems to be less than other datasets. Further, the Michigan dataset shows higher crash experience among respondents than other datasets.

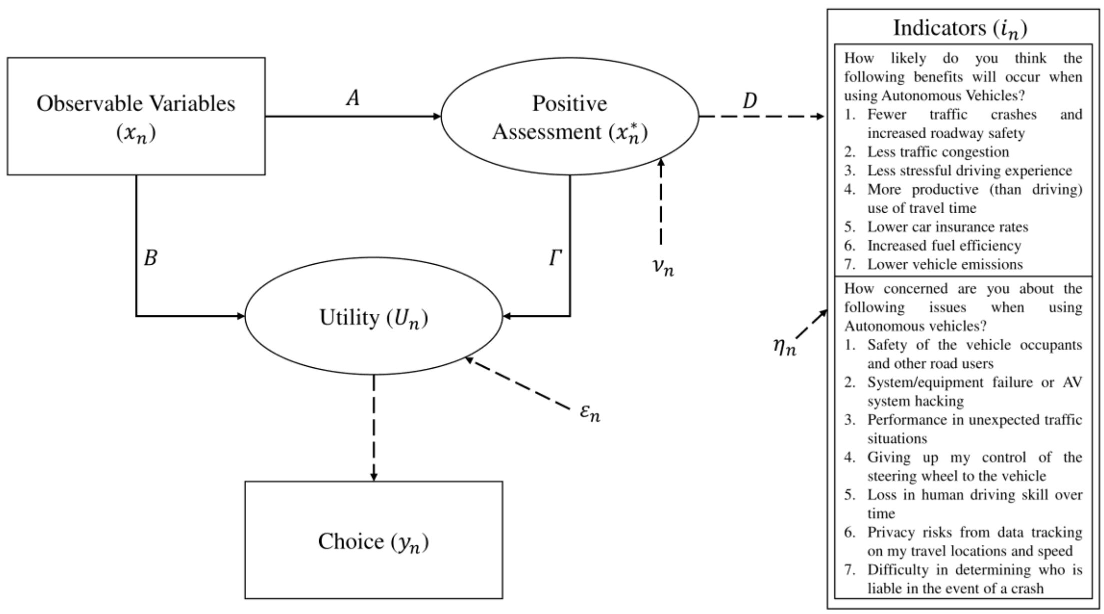
Table 1. Comparison of demographic characteristics between Florida, Non-Florida, Michigan and Non-Michigan regions

Variable name	Mean value

	Non-Florida	Florida	Non-Michigan	Michigan
Age in years	58.9	61.5	60	59.7
Female indicator (1 if the respondent is female, 0 otherwise)	0.40	0.41	0.40	0.34
Worker indicator (1 if the respondent is a worker, 0 otherwise)	0.58	0.49	0.53	0.62
Asian indicator (1 if the respondent is an Asian, 0 otherwise)	0.13	0.10	0.11	0.12
White indicator (1 if the respondent is white, 0 otherwise)	0.92	0.86	0.88	0.92
High income indicator (1 if the respondent's annual income is greater than $100,000)	0.30	0.24	0.27	0.33
Crash indicator (1 if the respondent had a crash experience)	0.75	0.72	0.74	0.83
Education indicator (1 if the respondent has a bachelor's degree, 0 otherwise)	0.70	0.65	0.69	0.65
Graduate indicator (1 if respondent's highest educational qualification is master's and age greater than 25 years, 0 otherwise)	0.40	0.35	0.37	0.32

With regards to the latent variables for the ICLV model (see Figure 2), this study models the positive assessment of the autonomous vehicles by the respondents as a latent variable, where socio-demographic information is used in the structural equation and 14 different indicators (7 each) related to perception of benefits of and concerns regarding autonomous vehicles are used in the measurement equation, where the response to the indicators is available on 5-point Likert-scale (extremely unlikely, unlikely, don't know/ can't say, likely, and extremely likely in the case of first set of indicators; and not at all concerned, not very concerned, don't know/ can't say, somewhat concerned, extremely concerned in the case of second set of indicators).

*** Insert Figure 10.2 ***



Caption: Integrated Choice and Latent Variable model with Positive Assessment of Autonomous Vehicles as Latent Variable

Credits: The chapter authors

With all the available information, ICLV and MNL models for non-Florida and non-Michigan are developed and discussed in detail in the next two sub-sections. The models are then applied to Florida and Michigan regions. The transferability assessment is carried out and the findings are discussed in the subsequent sections.

3.1 ICLV Models Results

Table 2a and Table 2b presents the structural models for the non-Florida and non-Michigan regions respectively. Results suggest that people in both regions with a past crash experience tend to be more favorable towards AVs. Similarly, non-Florida residents with at least a bachelor’s degree and working residents in non-Michigan are more likely to be in favor of AVs. Whereas, older non-Florida residents tend to be in less favor of using AVs.

Table 2a: Structural model of non-Florida ICLV model

Variable description	Parameter estimate
Age in years	-0.0077 (-2.57)
Crash indicator (1 if the respondent had a crash experience)	0.164 (1.82)
Education indicator (1 if the respondent has a bachelor’s degree, 0 otherwise)	0.107 (1.35)

Table 2b: Structural model of non-Michigan ICLV model

Variable description	Parameter estimate
Crash indicator (1 if the respondent had a crash experience)	0.165 (2.01)
Worker indicator (1 if the respondent is a worker, 0 otherwise)	0.130 (1.80)

Table 3a and Table 3b presents the choice models for the non-Florida and non-Michigan regions respectively. In both the regions, people who are in favor of AVs intend to use AVs either by owning or sharing. Also, residents in both regions with a graduate degree and older than 25 years intend to use AVs in either form. On the other hand, older people in both regions are less inclined towards using AVs in either form. Similarly, women in either region are more inclined to intend to not own AVs compared to sharing and not using. Non-Floridians with a past crash experience intend to use AVs in shared form rather than owning or not using them. Whereas the non-Michiganian with a crash experience intend to use AVs more likely in any of the either forms. Moreover, non-Michiganian Asians and people with higher income are more inclined towards using AVs in owning form. Finally, the non-Michiganian whites intended more often than non-whites to not use AVs in the sharing form.

Table 3a: Choice model of non-Florida ICLV model

Variable description	Owning an AV	Sharing an AV
Constant	2.90 (2.86)	2.30 (2.41)
Positive assessment latent variable	3.62 (11.34)	2.73 (8.69)
Age in years	-0.0174 (-1.59)	-0.0366 (-3.08)
Crash indicator (1 if the respondent had a crash experience)		0.475 (1.66)
Female indicator (1 if the respondent is female, 0 otherwise)	-0.344 (-1.76)	
Graduate indicator (1 if respondent's highest educational qualification is master's and age greater than 25 years, 0 otherwise)	0.501 (1.87)	0.615 (2.09)

Table 3b: Choice model of non-Michigan ICLV model

Variable description	Owning an AV	Sharing an AV
Constant	0.978 (1.34)	1.39 (1.86)
Positive assessment latent variable	3.50 (11.63)	2.68 (8.91)
Age in years	-0.0165 (-1.70)	-0.0347 (-3.25)
Asian indicator (1 if the respondent is an Asian, 0 otherwise)	1.09 (1.54)	
Crash indicator (1 if the respondent had a crash experience)	0.385 (1.44)	0.590 (1.89)
Female indicator (1 if the respondent is female, 0 otherwise)	-0.398 (-2.11)	
High income indicator (1 if the respondent's annual income is greater than $100,000)	0.139 (1.65)	
Graduate indicator (1 if respondent's highest educational qualification is master's and age greater than 25 years, 0 otherwise)	0.424 (1.66)	0.737 (2.67)
White indicator (1 if the respondent is white, 0 otherwise)		-0.607 (-2.04)

Table 4 presents the measurement model results. As expected, all the coefficients of assessment latent variable are positive for the benefit indicators and negative for the concern indicators.

Table 4: Measurement models of non-Michigan and non- Florida ICLV model

Indicator description		Parameter estimate	
		Non- Florida	Non-Michigan
How likely do you think the following benefits will occur when using Autonomous Vehicles?	Fewer traffic crashes and increased roadway safety	1.84 (17.01)	1.86 (17.38)
	Less traffic congestion	1.42 (17.74)	1.53 (18.11)
	Less stressful driving experience	2.24 (15.95)	2.21 (16.36)
	More productive (than driving) use of travel time	1.65 (17.41)	1.66 (17.67)
	Lower car insurance rates	1.14 (16.85)	1.29 (17.69)
	Increased fuel efficiency	1.26 (17.18)	1.33 (17.56)
	Lower vehicle emissions	1.04 (16.43)	1.16 (17.21)
How concerned are you about the following issues when using Autonomous Vehicles?	Safety of the vehicle occupants and other road users	-0.39 (-8.83)	-0.46 (-10.16)
	System/equipment failure or AV system hacking	-0.51 (-10.83)	-0.56 (-11.59)
	Performance in unexpected traffic situations	-0.42 (-9.17)	-0.49 (-10.59)
	Giving up my control of the steering wheel to the vehicle	-0.69 (-13.22)	-0.68 (-13.42)
	Loss in human driving skill over time	-0.66 (-12.90)	-0.59 (-12.26)
	Privacy risks from data tracking on my travel locations and speed	-0.60 (-12.01)	-0.54 (-11.44)
	Difficulty in determining who is liable in the event of a crash	-0.58 (-11.94)	-0.59 (-12.34)

3.2 MNL Models

Specifications of MNL models estimated in the Michigan and Florida regions are restricted to be the same as their corresponding ICLV choice model's specification to allow for a fair spatial transferability comparison between the different models. These locally estimated models are then used for the transferability assessment even if they included insignificant variables. Moreover, to check for the MNL model transferability performance in the presence of additional attitudinal information, aggregate measure of latent factors is fed into the model as described in section 2.3. The weights for the calculation of aggregate measures are extracted using PCA and are shown in Table 5. The estimation results of the MNL models with factors for non-Florida and non-Michigan regions are shown in Table 6a and 6b respectively. As expected, coefficients of the factors are statistically significant, and the signs are aligned with the coefficient of latent variables in the ICLV model.

Table 5: Extracted weights using principal component analysis

Indicator description		Weight	
		Non- Florida	Non-Michigan
How likely do you think the following benefits will occur when using Autonomous Vehicles?	Fewer traffic crashes and increased roadway safety	0.783	0.775
	Less traffic congestion	0.762	0.766
	Less stressful driving experience	0.811	0.797
	More productive (than driving) use of travel time	0.763	0.753
	Lower car insurance rates	0.692	0.714
	Increased fuel efficiency	0.721	0.731
	Lower vehicle emissions	0.675	0.701
How concerned are you about the following issues when using Autonomous Vehicles?	Safety of the vehicle occupants and other road users	-0.448	-0.503
	System/equipment failure or AV system hacking	-0.55	-0.576
	Performance in unexpected traffic situations	-0.474	-0.521

	Giving up my control of the steering wheel to the vehicle	-0.621	-0.615
	Loss in human driving skill over time	-0.601	-0.560
	Privacy risks from data tracking on my travel locations and speed	-0.568	-0.541
	Difficulty in determining who is liable in the event of a crash	-0.567	-0.576

Table 6a: Estimation results of non-Florida MNL model with factors

Variable description	Owning an AV	Sharing an AV
Constant	0.605 (0.97)	0.489 (0.69)
Assessment Factor	0.410 (13.92)	0.30 (9.94)
Age in years	-0.02 (-2.05)	-0.037 (-3.40)
Crash indicator (1 if the respondent had a crash experience)		0.509 (1.79)
Female indicator (1 if the respondent is female, 0 otherwise)	-0.218 (-1.16)	
Graduate indicator (1 if respondent's highest educational qualification is master's and age greater than 25 years, 0 otherwise)	0.443 (1.82)	0.576 (2.08)

Table 6b: Estimation results of non-Michigan MNL model with factors

Variable description	Owning an AV	Sharing an AV
Constant	0.194 (0.31)	0.745 (1.10)
Assessment Factor	0.392 (13.99)	0.294 (10.05)
Age in years	-0.0193 (-2.18)	-0.0364 (-3.62)
Asian indicator (1 if the respondent is an Asian, 0 otherwise)	1.37 (1.76)	
Crash indicator (1 if the respondent had a crash	0.572 (2.33)	0.736 (2.47)

experience)		
Female indicator (1 if the respondent is female, 0 otherwise)	-0.334 (-1.84)	
High income indicator (1 if the respondent's annual income is greater than $100,000)	0.174 (0.85)	
Graduate indicator (1 if respondent's highest educational qualification is master's and age greater than 25 years, 0 otherwise)	0.332 (1.41)	0.686 (2.61)
White indicator (1 if the respondent is white, 0 otherwise)		-0.591 (-2.02)

4. Transferability Assessment

For the transferability assessment, each of the Florida and Michigan datasets were randomly divided into 16 sets of estimation and validation datasets with an 80-20 proportion of observations respectively. ICLV and MNL models with factors from non-Florida and non-Michigan regions are then applied to the 16 validation datasets in the Florida and Michigan regions respectively. The transferred models were adjusted before transferring to the context regions. The alternative specific constants and scale in each model were iteratively adjusted [12] until they matched the observed shares in the transferring region's estimation dataset. For each of a study area's sixteen dataset partitions, the constant/scale adjusted models are then applied to each validation dataset to get the predicted shares.

Table 7 presents the calculated RATE values for non-Florida's and non-Michigan's ICLV, MNL and MNL model with factors transferred to their corresponding counter regions. The models seem fairly transferrable between the regions, as the six median RATE values (1.252, 0.992, 0.859, 1.072, 0.989 and 0.859) are close to 1. This suggests that both the transferred MNL and ICLV models are performing as good as their corresponding local models in terms of predictions. It can also be observed that the transferred ICLV model is not performing better than the corresponding other transferred MNL models. This result suggests that the ICLV models are not improving prediction but are at least replicating the prediction of market shares. Moreover, the MNL models seems to have better transferability when new information of latent factors is incorporated. This is important to note as it implies that there is helpful and transferable information available from the additional psychometric data on attitudes. Thus, if a latent variable could be replicated well, then it may be possible to improve the transferability of model with attitudinal data.

Table 7: RATE values for the transferred model and the corresponding application context model

Transferring Model	Transferring region	Application context model	Median	Mean
Non-Florida ICLV model	Florida	Florida MNL model	1.252	1.524
Non-Florida MNL model	Florida	Florida MNL model	0.992	0.991
Non-Florida MNL model with factors	Florida	Florida MNL model	0.859	0.912
Non-Michigan ICLV model	Michigan	Michigan MNL model	1.072	1.29
Non-Michigan MNL model	Michigan	Michigan MNL model	0.989	1.026
Non-Michigan MNL model with factors	Michigan	Michigan MNL models	0.859	1.392

5. Summary and Conclusions

This chapter explored the spatial transferability of ICLV models for gathering empirical support for the hypothesis that ICLV models may improve the transferability of travel behavior and travel demand models. Through a case study, the intention to use autonomous vehicles were modeled with ICLV models using demographic data and autonomous vehicle opinions. The models found support for the use of attitudinal data in modeling the choice of intended use. A positive assessment latent variable was modeled using the opinion data in a series of measurement equations by linking the correlation and directionality of those responses to demographic variables via a structural equation.

The case study explored the transferability of models estimated from Florida and Michigan datasets to non-Florida and non-Michigan states of the United States, respectively. This effort found that transferred MNL models perform better in terms of transferability when compared to the corresponding ICLV models. Additionally, when comparing performance between locally estimated MNL models to transferred ICLV models, predictive accuracy was very similar with nearly equivalent median RMSE values observed. This result does not provide support for the hypothesis of improved transferability in this case. Further research is needed to understand whether this is specific to this case study or a more general finding. This result fits in with Mariel's and Meyerhoff's suggestion that: "If model fit and predictive power are the goals, more simple models can be a more adequate choice" (p. 442) [22].

It is also possible that the MNL models exhibit better transferability (after updating the constants), simply because of the property that MNL models with updated alternative-specific constants can closely replicate aggregate shares of choice alternatives in the application context. The same property might not hold for the more advanced ICLV models. Notable in this regard is the question of whether transferability should be assessed without updating alternative-specific constants. Also, of relevance is whether predicted market shares should be the sole metric for assessing model transferability, or if other metrics such as elasticity measures should be used.

Additionally, there is an open question about whether opinions about new technology are transferable between regions. If these opinions are not transferable, then an ICLV is unlikely to transfer well since the structural and measurement latent variable equations likely would vary substantially between regions. In particular, opinions about new technology can be functions of familiarity, experience, and social norms. Since penetration rates of new technologies vary regionally, familiarity and experience likely would vary thus suggesting that attitudes could be limited in their transferability. The endogeneity involved with latent variables associated with attitudes could also increase the risk of poor transferability due to a break in casualty. Since casualty is a major factor in model transferability, solving issues with endogeneity/causalty inference is critical and likely means that there is no single answer to the question of if ICLV improve transferability. Efforts to prove the causality of particular latent constructs in travel choice, like those described by Chorus and Kroesen [20], would be a good next step in further assessing the viability of ICLVs for creating more transferable models.

The data used and modelled corresponds to intended usage of AVs (a technology that is not in the market yet) and not revealed preference data. Modelling such intended behaviors might be difficult with either the simple MNL or the advanced ICLV structures, due to various sources of uncertainty and bias (e.g., hypothetical bias in responding to questions of a futuristic travel technology, lack of details such as travel times and travel costs for the new travel technologies). Research on the topic of ICLV transferability might benefit from additional empirical evidence from modelling revealed behaviors.

Although support for improved transferability was not found, there were still encouraging results that support continued research and possible application. In particular, equivalent transferability to a local estimated MNL suggests that the non-linearity added, through the ICLV structural equation, is not overfitting the data. This suggests that it may be possible to use the transferred ICLV to conduct analysis that could not be done with the MNL model solely. Additionally, the results found that the psychometric data on attitudes did hold additional predictive power when incorporated directly as factor scores from a PCA.

A few more aspects are in need of further discussion here. First, there is a need for some guidance on choice of variables to be included in the structural equation of the ICLV model. Typically, demographic variables are the most sought-after variables but may only have a weak relationship with the latent variable. There is a need for better guidance on choosing (and collecting data on) relevant variables with strong relationships.

Second, it is known that the ICLV model can be reduced to a mixed logit model. However, there is no empirical evidence that mixed logit models are more transferable spatially than MNL models. If mixed logit models do not improve transferability, then it is unlikely that improved spatial transferability through ICLV could exist. However, if evidence of improved spatial transferability through mixed logit could be found, then it may be expected that the reduced form of an ICLV model could be an avenue for achieving higher spatial transferability. Mannering and colleagues [23] counter the criticism that mixed models tend to be less transferable by emphasizing that not accounting unobserved heterogeneity when it exists still leads to biased fixed parameter models. This bias will likely still lead to transferability issues even for the MNL model.

Thirdly, the transferability of models has been shown to increase when constants and scales are adjusted. This adjustment is straightforward for fixed coefficient models. But ICLV models include a latent variable which cannot be measured and thus mostly an ordinal and comparative stance can be used to compare people with different latent variable valuations. Is the distribution of a latent variable (and thus unobserved heterogeneity) between two areas expected to be similar? It is unclear whether adjustment of parameters in the latent variable structural equation could improve transferability but this may warrant further study.

Lastly, a limitation of this study for practical usage is that equivalent parameter sets for the models were tested between the ICLV and MNL. The MNL model was used for the basis of inclusion or exclusion of variables through the statistical significance of parameter estimates[2]. An ICLV model estimated in another region could suggest the retention of some variables through the use of the structural equation. There is no guarantee that a variable that is insignificant in an MNL estimation will produce insignificant estimates in a corresponding ICLV model. The combined non-linear effect from the latent variable structural model and the choice model may have a mean not significantly different than zero, but a component(s) of that non-linearity may be statistically significant when separated. Thus, an ICLV model may be able to guide itself to a reduced form choice model specification that would not have been considered by the analyst (when developing from a MNL base only) and possibly better fitted [11]. If this is the case, then it will be beneficial for regions that generally lack detailed attitudinal/perception data to borrow ICLV model from regions that have access to such detailed attitudinal/perception data to support the use of particular non-linear formulations.

6. References

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