EXPLORING TASTE HETEROGENEITY IN COMMUTING CYCLISTS' ROUTE CHOICE BEHAVIOR - EVIDENCE FROM TAIWAN

Ching-Fu Chen, Dept. of Transportation & Communication Management Science, National Cheng Kung University,E-mail:cfchen99@mail.ncku.edu.tw
Pei-Chun Chen, Dept. of Leisure Recreation & Travel Management, Toko University, E-mail:berylpooh@gmail.com

ABSTRACT

Developing sustainable transport systems has become an important goal in transportation planning and research in recent decades. Cycling is one of the most sustainable and environmentally friendly forms of transport. Many cities in the world now aim to become low carbon cities and focus on strategies to reduce car use and promote low carbon transportation modes, such as cycling, for commuting purposes. To achieve this goal, better understanding cyclists' preferences for cycling facilities, e.g., bicycle routes, is necessary. This project focuses on commuting cyclists' route choice behavior, and explores the issue of taste heterogeneity by applying the latent variable choice model (LVCM) and latent class model (LCM). The results of this research are expected to contribute to sustainable transport policy and management, and provide authorities with useful policy recommendations.

Keywords: *bicycle route choice, low carbon transport, sustainable transport, taste heterogeneity, stated preference method*

1.INTRODUCTION

Sustainable transport has become an important goal in transportation planning and research in recent decades (Chi & Stone, 2005; Hull, 2008; May & Crass, 2007). Cycling is one of the most sustainable and environmentally friendly forms of transport, and thus increasing attention has been paid to promoting it for commuting purposes. However, gaining higher rates of bicycle commuting depends upon various factors, such as improvements to the related infrastructure (Dill & Carr, 2003).

Due to the advantages of cars and motorcycles in terms of convenience, over 70% of commuters in Taiwan use motor vehicles, with only around 4 % traveling by bicycle (Ministry of Transportation and Communication of Taiwan, 2010). The resulting huge number of motor vehicles on the road causes severe conflicts with bicycles in a mixed traffic context. For example, the number of cyclists injured on the road in Taiwan increased from 7,448 in 2006 to 9,724 in 2008, and around 150 cyclists die in these accidents annually (National Police Agency of Taiwan, 2010). Therefore, cyclist safety has become an important issue for government policy makers and planners when promoting cycling as an alternative mode for commuting. As part of this, it is critical to obtain greater insights into cyclists' choice behaviour with regard to the routes they travel on.

Cycling safety has received considerable attention in the literature (Aultman-Hall & Adams, 1998; Doherty, Aultman-Hall, & Swaynos, 2000; Osberg, Stiles & Asare, 1998; Pucher & Dijkstra, 2000), and has been identified as a major determinant in the choice of bicycle route (Allen-Munley, Daniel & Dhar, 2004). A number of studies also confirm the significant effect that risk perception has on the choice of bicycle route (Bovy & Bradley, 1985; Hopkinson & Wardman, 1996; Wardman, Hatfield & Page, 1997).

The latent variable choice model (LVCM) has been developed to capture the impact of subjective factors on the decision processes,; these include not only tangible attributes, but also more intangible ones associated with a person's perceptions and attitudes, through the use of latent variables (Ben-Akiva et al. 2002). Daly, Hess, Patruni, Potoglou and Rohr (2012) argue that the use of latent attitudes in discrete choice models leads to an improved understanding of stated choice, and can be applied reliably in practical studies. Prato, Bekhor and Pronello (2012) consider latent variables (i.e., memory, habit, familiarity, spatial ability, time saving skills) alongside a traditional one (travel time) in a route choice model that was used to better understand travellers' behavior in urban transport networks. Although conceptually appealing, there are still rare applications of LVCM models in bicycle route choice behavior. Therefore, we adopt the LVCM by using risk perception as a latent variable to examine taste heterogeneity in commuting cyclists' route choice behavior in this study.

In addition, in order to consider unobserved heterogeneity, the latent class model (LCM) approach is also employed in this study. Compared to the MNL model for examining discrete choices, the LCM approach allows analysts to observe individual heterogeneity by characterizing various preference groups (Boxall & Adamowicz 2002; Louviere, Hensher & Swait 2000; Greene & Hensher, 2003).

This remainder of this paper is organized as follows. Section 2 reviews the factors affecting bicycle route choice. Section 3 presents the econometric models, followed by Section 4 on the experimental and survey design of the study. Section 5 reports the empirical results. Finally, Section 6 concludes the paper

2.FACTORS AFFECTING BICYCLE ROUTE CHOICE

Past studies have identified factors such as bikeway width, parking facilities, bicycle route type, traffic volume, speed limits, continuity, pavement quality, traffic stops, travel cost and travel time as affecting the choice of cycle route, along with personal characteristics (Bovy & Bradley,1985; Dill & Carr, 2003;Sener, Eluru & Bhat, 2009; Stinson & Bhat, 2003; Tilahun, Levinson & Krizek, 2007). Sener et al. (2009) investigated cyclist preferences and bicycle route attributes with an SP survey in Texas. They proposed that the relevant attributes included cyclist characteristics, on-street parking type, bicycle lane type, roadway grade, traffic volume, speed limit, and travel time.

Stinson and Bhat (2003) stated that the factors influencing bicycle route choice can be broadly categorized into link-level factors (e.g., pavement quality, bicycle facility type and bridge type) and route-level ones (e.g. travel time, number of red lights and continuity facility). Their results showed that travel time, bicycle facility, level of automobile traffic, and pavement or riding surface quality are the most important factors when choosing a route. Specifically, they find that cyclists are willing to endure additional travel time to use routes on residential streets and routes with a bicycle facility at bridge locations, rather than routes on minor and major arterial roads and those with no bicycle facility at bridge locations.

Hunt and Abraham (2007) investigated non-recreational cycling preferences and the influences of various factors on cycling behavior by estimating multinomial logit models using stated preference. Their results showed that the type of cycling facility, cyclist age, level of experience and comfort cycling in mixed traffic all had significant influences on cycling behavior. Larsen and El-Geneidy (2011) examined the personal factors that influence cycling facility usage, and how specific facility types and their characteristics affect route choice. They found that cyclists are willing to choose longer routes if they have facilities that are segregated from vehicle traffic.

In addition to bicycle facility attributes, personal attitudes and perceptions also affect the route choice behavior (Prato, Bekhor & Pronello, 2012), such as risk perceptions (Bovy & Bradley, 1985; Hopkinson & Wardman, 1996; Wardman, et al., 1997). Moreover, the design of bicycle facilities has a significant effect on perceived risk (Moller & Hels, 2008). For instance, if bicycle paths are separated from general roadways, so that cyclists can use them exclusively, then this obviously improves safety. Therefore, based on safety consciousness, bicycle route type is a very important attribute to consider when planning bicycle routes, especially for commuting cyclists. Nevertheless, the concept of risk perception has been still rarely applied when exploring cyclist preferences, and it is included in the current study.

3. METHODOLOGY

Random utility theory is the theoretical basis of discrete choice models (McFadden, 1974), and is used in this research. This theory starts from the assumption that individuals generate their behavior by maximizing the utility of their preferences, and it is used in this study to explain individual choices by specifying functions for the utility derived from the available alternatives. The utility function is estimated using a multinomial logit (MNL) model based on the premise that choices are consistent with an independence from the irrelevant alternatives (IIA) property. IIA indicates that the ratio of choice probabilities for any two alternatives for any individual is entirely unaffected by the systematic utilities of either of the alternatives. Assuming utility-maximizing behavior by the decision maker, the indirect utility function U_{ij} for each individual *i* who chooses alternative *j* in the choice set *Ci* can be expressed as:

$$U_{ij} = V_{ij}\left(X_{ij}, Z_i\right) + \varepsilon_{ij} = \beta X + \delta Z + \varepsilon_{ij} \qquad (1)$$

The utility function U_{ij} can be decomposed into the determinant part V_{ij} , which is typically specified as a function of deterministic components, including a vector of service attributes (X) and individual characteristics (Z). In addition, the error term ε_{ij}, which represents the unobservable individual characteristics, can influence choices (Louviere et al., 2000). Furthermore, in this study, β represents a vector of coefficients estimated for individual preferences on service attributes, and δ represents a vector of coefficients estimated for individual characteristics.

The dependent variable of Eq. (1) represents individual choice behavior and is a discrete variable. If $U_{ij}>U_{ik}$ for all $j \neq k$ in the choice set C_i, then the probability that individual *i* will select alternative *j* over *k* is given by:

$$P\left(j \mid C_i\right) = P\left(V_{ij} + \varepsilon_{ij} > V_{ik} + \varepsilon_{ik}\right) = P\left(V_{ij} - V_{ik} > \varepsilon_{ik} - \varepsilon_{ij}\right) \qquad (2)$$

The probability above depends on the hypotheses formulated about the distribution of the random vector of error terms. If the error term ε_{ij} is independently and identically distributed (IID), Gumbell distributions will occur across the population (Ben-Akiva & Lerman, 1985), and thus a standard logit model, or multinomial logit model (MNL), is applicable. With the MNL model, the probability $P(j\,|C_i)$ can be expressed as:

$$P_{ij} = \frac{\exp(V_{ij})}{\sum_{k \in C_i} \exp(V_{ik})} \qquad (3)$$

3.1 Latent class model

The latent class model (LCM) approach is also applied in the estimation. The LCM assumes that the population consists of a number of latent classes, *S*, and that the unobserved heterogeneity among individuals can be captured by these classes by estimating a different parameter vector in the corresponding utility function. Formally, the choice probability of individual *i* choosing alternative *j* of class *S* is expressed as:

$$P_i(j) = \sum_{s=1}^{S} P_i(j\,|\,S) \bullet H_i(S) \qquad (4)$$

Where

$$P_i(j\,|\,S) = \frac{\exp(V_{ij})}{\sum_{j' \in C_i} \exp(V_{ij})} \qquad (5)$$

$$H_i(S) = \frac{\exp(\theta_s' Z_i)}{\sum_{s=1}^{S} \exp(\theta_s' Z_i)} \qquad (6)$$

H_i denotes the prior probability for class *S* for individual *i*. Where Z_i is a vector of segmentation variables consisting of recreation specialization, θ is a vector of parameters for segment *s* (s = 1, 2, . . . , S).

Determination of the best number of segments requires a balanced evaluation of the indices, such as can be obtained using BIC (Bayesian Information Criterion) and AIC (Akaike Information Criterion). The most appropriate number of classes is usually the one that provides the minimum value of these measures (Boxall & Adamowicz, 2002). The related formulas are the follows:

$$AIC = -2(LL(\beta) - K) \tag{7}$$

$$BIC = -LL(\beta) + \left[\frac{K}{2}\ln(N)\right] \tag{8}$$

where LL(*β)* is the value of log-likelihood function at convergence, *K* is the number of parameters in the model, and *N* is the total sample size.

3.2 Latent variable choice model

Discrete choice models have traditionally presented an individual's choice process as a black box, in which the inputs are the observed attributes of available alternatives and individual characteristics, and the output is the observed choice. The resulting models directly link the observed inputs to the observed output, thereby assuming that the inner workings of the black box are implicitly captured by the model (Walker & Ben-Akiva, 2002). However, the psychological factors affecting decision-making generally are not included in the utility function, which results in poor explanatory power (Ben-Akiva et al. 1999). To address such issues, researchers have worked to enrich choice models by modeling the cognitive workings inside the black box, including the explicit incorporation of factors such as attitudes and perceptions. Ben-Akiva et al. (1999) propose the latent variable choice model (LVCM), which integrates the choice model and latent variable models, as shown in Figure 1. Each part consists of one or more structural equations and one or more measurement equations. The LVCM explicitly models the latent variables that influence the choice process. Structural equations relating the observable explanatory variables *X* to the latent variables X^* model the behavioral process by which the latent variables are formed. While the latent constructs are not observable, their effects on indicators are. The measurement equation model is used to link the latent variables X^* to indicators *I*.

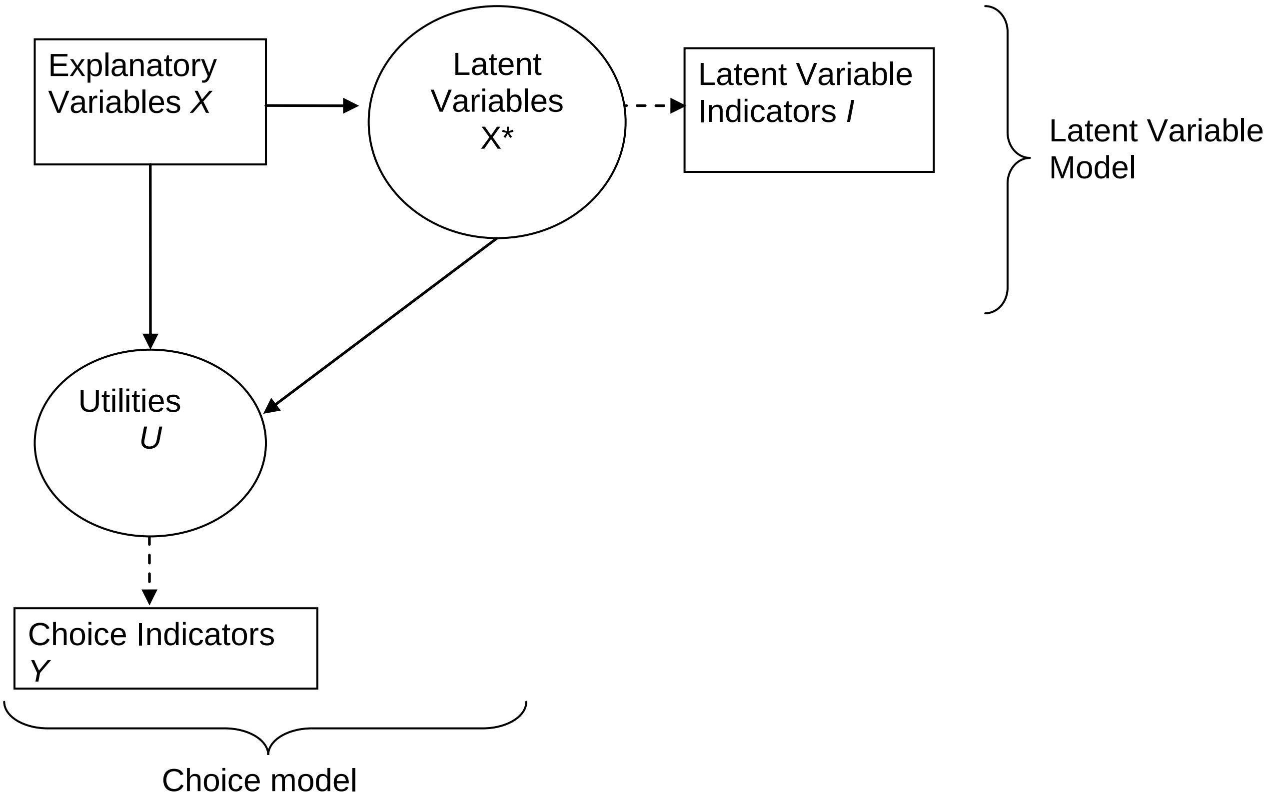

Figure 1. Integrated choice modeling framework (Walker & Ben-Akiva, 2002)

EXPERIMENTAL AND SURVEY DESIGN

For the choice experiment design, the most relevant attributes for bicycle facilities are identified based on review of the literature (Bovy & Bradley, 1985; Hopkinson & Wardman, 1996; Tilahun et al., 2007; Stinson & Bhat, 2003; Sener et al., 2009) and a pilot survey. Table 1 summarizes the attribute-level specifications for the choice experiment. The attributes include route type, traffic volume, traffic stop signs, and travel time.

The questionnaire consists of three parts. Part 1 consists of a choice experiment. Route type (i.e. bike path, bike route, and bike lane) is used to define alternative specific constants (ASCs). An orthogonal fractional factorial design was constructed using SPSS17.0 (SPSS Inc., 2008) that contained only a small subset of nine of choice sets, which were randomly split into three versions, each with three different choice sets composed of various levels of attributes. Respondents were provided with descriptions of three choices (i.e. choice A: bike path, choice B: bike route, and choice C: bike lane). An example choice set is presented in Figure 2.

Table 1. Facility attributes and levels

Facility attributes	Levels
Route type	Bike path Bike lane Bike route
Traffic volume	1. light 2. moderate 3. heavy
Traffic stop signs	1.1-2 2. 3-4 3. High >5
Travel time	10 min 15 min 20 min

Route / Attributes	A	B	C
Route type	Bike path 	Bike lane 	Bike route 
Traffic volume	moderate	light	light
Traffic stop signs	>5	3-4	1-2
Travel time	20 min	20 min	10 min
Option	☐	☐	☐

Figure 2. An example choice set

Part 2 has six items and deals with those measurements of risk perception pertaining to the cognitive and emotional dimensions (Møller and Hels 2008). The cognitive dimension was assessed by three items using a five-point Likert type scale ranging from 1 (= very low) to 5 (= very high). The questions related to the cyclist's risk of being involved in an accident, such as "risk of being involved in an accident riding on a bike path", "risk of being involved in an accident riding on a bike lane", and "risk of being involved in an accident riding on a bike route". The emotional dimension was addressed by asking respondents three items that consisted of questions concerning perceived danger on different bike routes such as "perceived danger level riding on a bike path", "perceived danger level riding on a bike lane", and "perceived danger level riding on a bike route". This was measured with a five-point Likert scale, ranging from 1 = "very low" to 5 = "very high". Finally, Part 3 included questions about respondent characteristics, such as gender, age, marital status, occupation, personal monthly income, and education level.

A self-administered questionnaire was used to collect data for empirical analysis, with 300 questionnaires delivered to cyclists who ride bicycle for commuting purposes based on a convenience sampling technique during the period from January to February 2012. An on-site survey was conducted at various well-known bicycle routes in Tainan City and KMRT stations in Kaohsiung City. After eliminating incomplete responses, 217 useable questionnaires were obtained, yielding a 72.3% response rate.

The majority of the sample was male (62.2%), and 78.3% were single. Around half of respondents (49.3%) held a university degree, while 62.7% had a monthly income under NT$20,000 (US $625), and 61.3% were students. Around 40.1% of the respondents were aged 19-25, followed by those aged 31-35 (20.7%).

4. RESULTS

4.1 **Latent variable choice model**

The latent variable choice model consists of measurement equations and structural equations. Measurement equations are used in the estimation to provide identification of the latent constructs and further estimates for structural equations. Confirmatory factor analysis is conducted to analyze the validity and reliability of the latent constructs. Estimates of the measurement equations are presented in Table 2. Goodness of fit indices include χ2=26.21, df =6(p<0.001), χ2/d.f. =4.36, RMSEA = 0.09, GFI = 0.96, CFI =0.97, and NFI=0.92.

/ insert Table 2 about here/

Table 2. Estimates of the measurement equations of the latent variable model

Variable	Risk 1 - Cognitive		Risk 2 - Emotional	
	Estimate	T value	Estimate	T value
Risk-C1	1.00	--		
Risk-C2	0.67	10.84		
Risk-C3	0.50	7.77		
Risk-E1			1.00	--
Risk-E2			0.73	9.11
Risk-E3			0.30	4.07

In terms of the structural equations, socio-demographic characteristics are used as explanatory variables for the latent variable of risk perception. As shown in Table 3, younger respondents reported higher cognitive and emotional risk, while respondents with more cycling experience reported less perceived cognitive risk. Having obtained a university degree and being married were both related to higher perceived emotional risk. Finally, frequently cycling was linked to higher emotional risk.

Table 3. Estimates of the structural equations of the latent variable model

Variable	Risk1-Cognitive		Risk2- Emotional	
	Estimate	T value	Estimate	T value
Constant	3.12	105.17**	2.73	72.70**
Age(18-25)	0.19	5.45**	0.12	3.42**
Marriage(Married)	-	-	0.12	2.84**
Education(University)	-	-	0.17	5.44**
Frequency(>5 times)	-	-	0.10	3.31**
Experience(>4 years)	-0.13	-3.76**	-	-
R^2	0.02		0.03	
Adj- R^2	0.02		0.02	
F -value	21.34**		12.72**	

Estimates of the choice models are presented in Table 4. The first model (MNL1) is the base model, as it does not include the effects of the interaction terms. The second model (MNL2) is the model with interaction terms in an attempt to capture the systematic heterogeneity. Model LVCM contains interaction terms and latent variables in the choice model. Most of the results from the three models are similar. In the analysis, the bike route is treated as the base route. Therefore, ASCs are estimated only for the bike path and bike lane. The ASC_Path for all three models is positive and significant, indicating that cyclists prefer to use bike paths. However, the coefficients of ASC_Lane are only significantly positive for the MNL1 and LVCM models, indicating that cyclists are likely to use bike lanes.

The results of three models indicate the parameters of traffic volume, stop signs, and travel time are estimated significantly with negative signs, suggesting that respondents prefer lower traffic volume, fewer stop signs, and less travel time. In addition, MNL2 is the model with interaction terms between the socio-demographic and alternative-specific constants. The coefficient of MAG*ASC_Lane is significant and positive. This suggests that married respondents are more likely to use bike lanes. Regarding the LVCM model, the parameter estimates of the interaction terms between the latent variables and alternative-specific constants suggest that the respondents with high levels of emotional risk are more likely to use bike paths. In terms of explanatory power, all three models have a satisfactory goodness-of fit, with an explanatory power $\rho 2$ of 0.20.

/insert Table 4 about here/

Table 4. Estimate results of the route choice model

Attributes	MNL1		MNL2		LVCM	
	Estimate	T value	Estimate	T value	Estimate	T value
ASC_Path	0.94	7.90**	0.68	2.34*	0.95	7.80**
ASC_Lane	0.43	3.48**	-0.27	-0.86	0.48	3.79**
Traffic volume - Moderate	-0.54	-4.99**	-0.53	-4.81**	-0.53	-4.85**
Traffic volume - Heavy	-1.59	-10.85**	-1.61	-10.89**	-1.57	-10.73**
Stop signs - Moderate	-0.84	-5.65**	-0.79	-5.22**	-0.76	-5.01**
Stop signs - High	-0.13	-0.97	-0.09	-0.65*	-0.07	-0.48
Travel time	-0.14	-9.03**	-0.14	-8.85*	-0.14	-9.23**
Interaction						
GEN* ASC_Path			0.14	0.60		
MAG* ASC_Path			0.67	1.81		
OC* ASC_Path			-0.11	-0.25		
AG* ASC_Path			0.22	0.55		
GEN* ASC_ Lane			0.30	1.18		
MAG* ASC_ Lane			0.90	2.35*		
OC* ASC_ Lane			0.68	1.35		
AG* ASC_ Lane			-0.09	-0.18		
Risk- CO* ASC_Path					-0.09	-0.77
Risk- EM*ASC_Path					0.26	2.10*
Risk- CO * ASC_Lane					0.00	0.02
Risk- EM * ASC_Lane					-0.00	-0.03
LL(β)	-552.47		-547.03		-548.78	
LL(0)	-686.44		-686.44		-686.44	
Likelihood ratio index ρ^2	0.20		0.20		0.20	

5.2 Latent class models

The LCM model is used to identify different characteristics of commuting cyclists based on variations in taste with respect to facility attributes. In this paper, we attempt to capture heterogeneity by categorizing classes with regard to commuting the cyclists' different levels of risk perception and facility attributes. To identify the number of latent classes to be used in the analysis, the Bayesian Information Criterion (BIC), Akaike Information Criterion (AIC) (Boxall & Adamowicz 2002) and likelihood ratio index are used to evaluate the performance of various models (Walker & Li 2007). Two, three, and four-segment solutions are reported in Table 5. The four-segment solution is preferred because it has the lowest AIC, highest likelihood ratio index, and in examining the estimation results, it provides the most satisfying behavioral interpretation.

/insert Table 5 about here/

Table 5. Criteria for determining the optimal number of segments

Number of class	Parameters	Log likelihood value	AIC	BIC	ρ^2
2	15	-538.95	1107.90	579.30	0.21
3	23	-525.29	1096.58	587.16	0.23
4	31	-511.46	1084.92	594.85	0.25

Table 6 presents the estimation results for the four-segment latent class model, including the latent variable of risk perception in the segment membership function. Segment 4 is used as a base, and all of the membership coefficients in Segment 4 are normalized to zero. The estimates of risk perception variables for other segments are interpreted relative to Segment 4. The results from the LCM model suggest that there is considerable heterogeneity among the cyclists' preferences. Almost all the parameters have significant signs that are consistent with the MNL models. Differences in the influences on segment membership and tastes across the segments are noticeable. The LCM model has a higher goodness-of-fit compared to the MNL and LVCM models, with an explanatory power ρ2 of 0.26. The LCM results reveal significant heterogeneity in cyclist preferences across latent classes, with associated class membership probabilities of 36.5%, 32.1%, 24.4%, and 7%. The respondents are assigned to one of the segments on the basis of their largest probability score.

The results reveal that respondents in segments 2 and 3 have higher levels of risk perception in the cognitive dimension than those in segments 1 and 4. The

ASC_Path and ASC_Lane are estimated significantly with positive signs in segments 2 and 3, suggesting that respondents in these segments are more likely to prefer bike paths and bike lanes. More specifically, respondents in segment 3 are more likely to prefer bike paths, while those in segment 2 were more likely to prefer bike lanes.

Respondents in segment 1 are more sensitive to moderate numbers of stop signs than heavy traffic volume. Respondents in segment 2 are highly sensitive to traffic volume, stop signs and travel time, and prefer less traffic volume and less travel time, but can accept a moderate number of stop signs along the bicycle route. Segment 3 is composed of cyclists who are highly sensitive to travel time and have higher levels of risk perception in the cognitive dimension (i.e., cognitive judgement about the risk of being involved in an accident). Segment 4 comprises the smallest percentage of cyclists, who are not sensitive to any of given attributes.

Table 6. Results of latent class models

Attributes	Segment 1		Segment 2		Segment 3		Segment 4	
	Estimate	T value	Estimate	T value	Estimate	T value	Estimate	T value
Utility function								
ASC_Path	0.77	1.67	2.35	7.97**	2.82	5.10**	-21.63	-0.12
ASC_Lane	0.93	2.25*	1.42	5.66**	0.92	2.00*	-4.76	-0.14
Traffic volume - Moderate	-0.35	-0.98	0.19	1.13	-2.72	-6.71**	12.46	0.08
Traffic volume - Heavy	-1.98	-5.34**	-0.76	-3.84**	-4.26	-8.79**	-0.96	-0.03
Stop signs - Moderate	-1.71	-3.47**	0.61	2.18*	-3.94	-5.65**	-16.67	-0.10
Stop signs - High	-0.44	-1.22	-1.10	-5.29**	-1.46	-3.99**	-13.99	-0.10
Travel time	-0.40	-4.67**	-0.10	-3.93**	-0.19	-4.04**	4.21	0.09
Segment function								
Constant	1.56	3.78**	1.58	4.32**	1.21	2.56*		
Risk- CO	-1.18	-0.44	0.77	2.07*	1.07	2.25*		
Risk- EM	-0.60	-1.50	-0.17	-0.43	-0.29	-0.68		
Class probability	36.5%		32.1%		24.4%		7%	
LL(β)	-505.74							
LL(0)	-686.44							
Likelihood ratio index ρ^2	0.26							

6. CONCLUSIONS

This paper analyzed commuting cyclists' preferences for attributes of bicycle route facilities in Taiwan. The SP method was used in this work, in which commuting cyclists were asked to state their choice from three alternative bicycle routes on the basis of their attributes. Choice modeling was applied to the collected data, and cyclists' preferences for each attribute were estimated. This study used MNL models, which included facility attributes and ASC interactions with the risk perception variables, to capture the systematic heterogeneity in commuting cyclists' preferences. In addition, risk perception variables were used to capture observed taste heterogeneity in the preference of bicycle route and facility attributes using the LCM model. The LVCM model was used to identify cyclists' risk perceptions in the preference of bicycle route choice.

The empirical results of the MNL model indicate that commuting cyclists prefer lower traffic volume, less stop signs, and less travel time. These results confirm previous findings in the route choice behavior literature (Sener, Eluru & Bhat, 2009; Stinson & Bhat, 2003). Estimating the LVCM model contributes to the understanding of the determinants of cyclists' risk perception in route choice behavior. The findings suggest that cyclists generally prefer bike paths, bike lanes, lower traffic volume, less stop signs and less travel time, but also that their risk perceptions significantly influence their preferences. The results of the LVCM model suggest that commuting cyclists with high levels of emotional risk are more likely to use bike paths.

According to the results of the LCM model, high risk perception cyclists are more likely than low risk perception cyclists to choose bike paths. The results of the estimated LCM model provide evidence of significant heterogeneity in bicycle route choice behavior in the high risk perception group. Specifically, the LCM model identified market segments in terms of access facility attributes and respondents' characteristics. Each segment has a unique set of taste parameters to capture preference heterogeneity across individuals. The results derived from the LCM model show that it is able to systematically reveal the heterogeneity of risk perceptions, and their relation to route choice behavior. The use of the LCM model significantly improves the goodness-of-fit relative to the MNL and LVCM models, indicating that the way of modelling the route choice must account for individual heterogeneity.

As expected, cyclists prefer effective, comfortable and safe routes for their journeys. Supplying an infrastructure which offers cyclists a quick, comfortable and safe link during every trip is thus an essential precondition for a successful cycling policy (CROW, 1993). However, if cycling is to be made even safer, then this requires not only an improved infrastructure, but also thorough education for cyclists, drivers and pedestrians.

There are some limitations to this study that suggest future research directions. First, this survey only focused on commuting cyclists' route preferences, and more bicycle facility attributes could be evaluated in further studies. Second, this study used risk perceptions as a segmentation variable to explore the heterogeneity in cyclists' preferences. Future research could investigate other segmentation variables, and test the resulting heterogeneity in cyclists' preferences.

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