CHOICE OF MICRO-MOBILITY: CASE STUDIES OF A PUBLIC BICYCLE SHARING SYSTEM IN NEW ZEALAND

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ABSTRACT

This study considers how to improve understanding of sustainable urban transport planning from the perspective of the Central Business District (CBD) redevelopment process for two cities, Hamilton and Christchurch in New Zealand (NZ). The most proportion of 'Public Bicycle Share Schemes' operate in densely populated cities as these are characterized by limited modal accessibility but high population density in the urban CBD. This situation is similar to NZ's two medium-sized cities, in each of which the city's population density is constantly increasing in the past years. In this study, Multinomial and Mixed Logistic regression models were used to determine the model specification, and subsequently, to test the mode choice cross-elasticities for promoting greater use of the bicycle sharing system in conjunction with public transport service. The data were gathered using stated preference surveys from 486 New Zealanders, and the modeling results indicate that the potential improvement in a modal shift towards micro-mobility, which can be enhanced by applying different policy options.

Keywords: Public Bicycle Share Scheme, Micro-mobility, Stated Preference Survey, Logistic Regression Model, New Zealand

1. INTRODUCTION

Providing active transport opportunities to increase connectivity between people and places to support safe, healthy, and liveable communities has been controversial in many cities in the world. The transformation from the passive to active transport modes is a process, which involves addressing the levels of inactivity in a population and replacing car trips by walking and cycling; and reducing air and noise pollution to enhance the sustainable urban environment. According to Statistics NZ (2019), Christchurch and Hamilton are New Zealand (NZ)'s third and fourth largest cities and also among the fastest-growing urban areas with a combined total population of 555,000 in 2017. Since 2006, these two cities have accounted for more than 14% of the country's population growth and they are projected to reach 683,000 by 2043 (Statistics NZ, 2019). Currently, the local and central government are promoting cycling in the city by developing connected cycle networks to allow residents to cycle more easily.

In NZ, Bicycle Sharing Systems (BSS) has been introduced to Auckland's central business district (CBD) by private companies since 2013 as a transport option. A BSS is a transport mode which provides short-term use of a bicycle either free or low service charge for users. The system operates by allowing users to collect bicycles from exclusive bicycle stands called 'docks' then return the bicycle to another dock closer to their destination. These docks have a special mechanism, which only releases via computer control. The 'dockless' or 'free-floating' is another platform of the bicycle share system in which the user collects a bicycle by using a smartphone mapping app. The process allows for authenticated payment usually achieved through a smartphone app to unlock the bicycle for the user. StatsNZ predicts that NZ's urban population will increase during the next decade, so there is going to be a higher travel demand for urban transport especially with congestion on roads, and resultant travel delays, becoming major issues (Statistics NZ, 2019).

This study develops the concept of integrating BSS and existing public transport services (bus and rail) in the CBDs of two medium-sized cities, Christchurch and Hamilton, and examines whether it is a viable transport option to extend the reach of the public transport network. The benefits of the system are the opportunities around the CBDs for public access to reduce the travel time through micro-mobility such as bicycles and E-scooters. This enhancement also benefits the environment by reducing carbon dioxide emissions, improves personal well-being by increasing the active transport mode share, and eases congestion by reducing road traffic.

Christchurch and Hamilton are ideal cities for bicycle sharing. NZ government have supported and developed its infrastructure to promote cycling and walking as an attractive transport option. Over the past few years, the level of service has increased for cycling in NZ cities. Separate cycle lanes and traffic signal priorities have enabled cyclists to feel safer and more comfortable on roads, whereas the more CBDs has established restricted access and parking for vehicles. Introducing a Public Bicycle Sharing Scheme (PBSS) in the CBD could be a sustainable and effective means of improving the urban transportation system as it would promote the modal shift among users from vehicles to public transport.

For this study, the primary focus is to investigate how to strengthen the benefits to users of the public transport system by integrating the BSS and public transit. In addition, this study investigates how to improve the intermodal connectivity of the urban transport system and flexibility for public transport users by providing different point-to-point transport options.

2. PUBLIC BICYCLE SHARING SCHEME

A PBSS is a mobility service, also referred to as 'public use bicycles', 'bicycle transit', 'bicycle sharing', or 'smart bicycle', which allows citizens to rent and return bicycles in areas where the scheme is operated without the responsibilities of bicycle ownership (Midgley, 2011). While these schemes have been operated for over 50 years, they are still growing and developing globally (Shaheen et al., 2010). Public bicycle sharing schemes have been combined with technology to encourage more people to ride bicycles and to utilize the public transport system. By introducing GPS, the movement of users has become available to be checked in real-time and to prevent vandalism and theft. By introducing online services, such as websites and smartphone apps, people have become able to check the location and number of available public bicycles, docks and to pay the rental fee more easily (Fishman et al., 2013).

The main benefit of a PBSS is to promote clean air by reducing traffic emissions from vehicles. It is expected to provide a healthier lifestyle to citizens. Encouraging people to ride bicycles rather than to drive cars creates more space on the roads, as a bicycle can be expected to be an alternative to other means of transportation, thereby easing traffic congestion (Dhingra & Kodukula, 2010). Interestingly, although the PBSS system has been growing and offers evident advantages, not all schemes have succeeded due in particular to failures in intermodality between them and other forms of public transport such as existing bus and rail system. For the last few decades, there have been many cities that have introduced PBSS to their CBDs internationally. A literature review on small and medium-sized cities with a similar population to Christchurch and Hamilton reflected how inter-modal connectivity and flexibility were essential factors in developing the PBSS in less dense urban areas.

The case study of the two medium-sized cities enabled the development of ideas about how PBSS could be promoted more effectively in the high-density area at lower density urban cities with a population of between 250,000 and 500,000. This could also be seen as a strategic option for local and central governments to develop the urban transport systems in their transport network as means to promoting cycling as a viable transport option with benefits for public health and the environment.

3. METHODOLOGY

3.1 Logistic Regression Model

The logit model was first derived by Luce (1959) and it is the most widely used model because of the fact that the choice probabilities take a closed-form and can be interpreted readily. In the multinomial logit model (MNL), the probability that the choice outcome y_i is alternative j from all alternatives available can be expressed as the logit formula:

$$P(y_i = j) = P_{ij} = \frac{\exp(x_i\beta_j)}{\sum_{k=0}^{J}\exp(x_i\beta_k)} \text{ for } j = 0, \dots, J \quad (1)$$

The vector β_j is a vector or coefficients specific to the j th alternative, x_i is a vector of characteristics specific to the i th individual, y_i is a random variable that indicates the choice made. To identify the model, we assume without loss of generality that $\beta_0 = 0$. The model can also be written in terms of the odds for each pair of options j and q:

$$\Omega_{ij|iq} = \exp(x_i[\beta_j - \beta_q]) \quad (2)$$

This equation shows that the odds of choosing j verses q do not depend on which other outcomes are possible; the odds are determined only by the coefficient vectors for β_j and β_q. Assuming that unobserved utilities for each alternative are independently and identically distributed (IID) and are described by the Extreme Value Type 1, distribution produces the MNL model (Domencich and McFadden, 1975). The utility functions are usually linear in the parameter forms, and the parameter x is related to the variance of ε (Ben-Akiva and Lerman, 1985). Thus, for the MNL model, $\beta^2 = \pi^2/6\sigma^2$. The key assumption of the MNL model is that the errors are independent of each other. This independence means that the unobserved portion of utility for one alternative is unrelated to the unobserved portion of utility for another alternative. If one thinks that the unobserved portion of utility is correlated with that of alternatives, then there are three options (Train, 2003): (1) use a different model that allows for correlated errors, such as the nested logit or mixed logit model, (2) re-specify the representative utility so that the source of the correlation is captured explicitly, and thus the remaining errors are independent, or (3) use the logit model under the current specification of representative utility, considering the model to be an approximation. The MNL model was the most widely used modeling methodology to measure transport users' mode choice behavior in the bicycle sharing system (Cambell et al., 2016; Fishman et al., 2015; El-Assi et al., 2017).

The mixed logit model (ML) is a flexible discrete choice model that can approximate any random utility model (McFadden and Train, 2000; Hensher, 2001). Recent advances in discrete choice modeling, have promoted the treatment of attitudes and perceptions affecting decision-making to get a more realistic representation of the choice behavior. The ML model generalizes the MNL by allowing the coefficients of observed variables to vary randomly between people rather than being fixed. Partitioning the stochastic component of the random utility equation into two additive parts (i.e., uncorrelated) allows for the possibility that the information relevant to making an unobserved choice may indeed be sufficiently rich in reality to induce correlation across the alternatives in each transport mode choice situation. One part is correlated over alternatives and is heteroscedastic, and another part is independently, identically distributed over alternatives and individuals, as follows.

$$U_{ij} = \beta X_{ij} + \vartheta_{ij} + \varepsilon_{ij} \quad (3)$$

where X_{ij} is a vector of coefficients that is observed variables and related to each individual i and alternative j, β is a vector of parameters, ε_{ij} is once again a random term (with zero mean) that is independently and identically distributed over alternatives and individuals, and ϑ_{ij} is an error component that can be correlated among alternatives and heteroscedastic for each individual. The mixed logit model assumes a general distribution for ϑ_{ij} and an IID Gumbel distribution for ε_{ij} (Hensher and Greene, 2002). The density function of the error component ϑ_{ij} is denoted as $f(\vartheta_{ij}|\tau)$, where τ is a parameter vector of the distribution of ϑ_{ij}. The conditional probability of choosing option j given the value of the component ϑ_{ij}, is

$$Q_i(j|\vartheta_{ij}) = P_{ij} = \frac{\exp(x_{ij}\beta + \vartheta_{ij})}{\sum_{k \in Z_i}^{J}\exp(x_{ik}\beta + \vartheta_{ij})} \quad (4)$$

Since ϑ_{ij} is not given, the unconditional choice probability, $P_i(j)$, is the integral of the conditional choice probability, $Q_i(j|\vartheta_{ij})$, over the distribution of ϑ_{ij}. This model is called the mixed logit (ML) model since the choice probability is a mixture of logits with $f(\vartheta_{ij}|\tau)$ as the mixing distribution (Hensher et al., 2005). In general, the ML model does not have an exact likelihood function because the probability $P_i(j)$ does not always have a closed-form solution. Therefore, the ML model uses simulated maximum likelihood estimation for computing the approximate probability (McFadden and Train, 2000).

3.2 Revealed Preference and Stated Preference Survey

This study investigated how to design a PBSS system in CBDs facilitating inter-modal connectivity and flexibility for public transport passengers so that a PBSS can be made a viable micro-mobility option for residents in Christchurch and Hamilton. The following two case studies could be used to make user-specific recommendations and help policymakers apply PBSS effectively in their urban transport network.

In order to develop PBSS in Christchurch and Hamilton, a Revealed Preference (RP)/ Stated Preference (SP) survey was developed to obtain the sociodemographic information of public transport users and their perception of new transport options. The survey aimed to determine whether PBSS would meet the level of service requirements and fit the demand for the two cities' social and economic demographics. A discrete survey was used, where randomly selected individuals were invited to complete a choice set. The RP/SP survey was divided into two sections:

- Section 1 (RP) – Socioeconomic information and current travel behavior
- Section 2 (SP) – Hypothetical choice experiments including two alternative options for PBSS

Section 1 detailed the user's sociodemographic profiles, which included the participant's age, gender, relationships, trip purpose to CBD, education, income, and most frequent mode of transport when visiting the CBD area.

Section 2 detailed eight hypothetical scenario-based choice questions based on three options with three factors influencing travel behavior. These included three modes after catching a bus and then either walking (Status-Quo), biking with a traditional bicycle or E-bicycle for 1 km to the destination. The three options were:

- Option 1 (SQ: Bus + Walk) – User has to exit the bus and walk for 1 km to the destination, which takes 15 minutes
- Option 2 (Bus + traditional bicycle) – User has to exit the bus and to ride a traditional bicycle for 1 km to the destination, which takes 7 minutes
- Option 3 (Bus + E-bicycle) – User has to exit the bus and to ride an E-bicycle for 1 km to the destination, which takes 5 minutes.

The three attributes investigated were:

- Service Cost ($/hour) – total fare (e.g., bus fare + bicycle service fare)
- Bicycle Accessibility (meters) – walking distance to the bicycle station and from another bicycle station to destination
- Bicycle Availability (%) – the likelihood of finding a bicycle at the bicycle station.

As part of the scenario, the service cost attribute had three levels ($2.40, $2.65 and $2.90) with the medium price being the base price. The bicycle stations were 25-50 meters away from the bus stop and from the destination, which implies 45 to 90 seconds of walking time respectively. For measuring the bicycle accessibility, two levels of the value, less than 25 meters for the lower value and 50 meters walk distance to pick up or drop off the bicycle as the higher value, were used in the choice experiments. Two attribute levels, 50% and 75% for the availability of a traditional bicycle and 75% and 100% for an E-bicycle, were used for all choice experiments.

4. SAMPLE ANALYSIS

During October 2018, a pilot study of the RP/SP survey was conducted to test the survey structure and the validity of the experimental design. The sample used for the study consisted of 184 participants from Christchurch and 301 from Hamilton who were approached at random and were asked to complete the survey. In total, there were 3,880 observations of transport mode choice collected from two cities, and the results are shown in Table 1.

Table 1. Sample Demography

	Christchurch	Hamilton
Gender		
Male	97	135
Female	87	166
Age		
Under 18	19	40
19-29	75	126
30-39	38	69
40-49	21	35
50-59	20	18
60-69	7	7
Over 70	4	6
Purpose of trip to CBD		
Work	54	75
Education	54	103
Shopping	26	61
Home	9	16
Leisure/entertainment	36	44
Other	5	2
Education		
No degree	18	39
High school/Diploma	56	94
Vocational/Trade school	16	27
College/Associate degree	48	77
Four-year degree or higher	46	64
Individual income bracket		
Less than 12,000 NZD	54	101
12,000-24,999 NZD	24	78
25,000-39,999 NZD	28	50
40,000-74,999 NZD	56	54
75,000 NZD or more	21	18
Mode of transport to CBD		
Bus	85	135
Car	57	139
Bicycle	21	6
Walk	21	21
Total Respondents	184	301

The following sociodemographic characteristics are found to be relevant in terms of the study sample from Christchurch and Hamilton:

- Majority of participants were 19 to 29 years of age
- Most of the participants were educated to high-school or university level
- Approximately 46% of participants never had married or were single

- The highest number of participants were earning under $25,000 in Hamilton while there were relatively high-income respondents from Christchurch.
- In terms of mode choice, the purposes of most trips to CBD were commuting to either education or work.
- The current options for the modes of transport to both Christchurch and Hamilton CBD include bus, bicycle, car and walk, with either bus or car were the most frequent modes.
- The modal share for active transport such as walking and bicycling was around 22% of the total share for Christchurch and only 9% for Hamilton. The mode share for public transport was around 45% for both cities indicating that introducing PBSS to the CBDs could attract more public transport users for providing better intermodal connectivity.

5. MODELING RESULTS

This section describes the mode choice models obtained for respondents from the two cities. Multinomial logit (MNL) and mixed logit (ML) models were estimated using three generic attributes (cost, bicycle accessibility, and availability) plus the six socio-economic attributes. The MNL and ML models were estimated using the 1,472 observations from 184 survey respondents from Christchurch and 2,408 observations from 301 survey respondents from Hamilton with separate utility functions for each mode (SQ: Bus + Walk, Option 1: Bus + Traditional bicycle, Option 2: Bus + E-bicycle). Estimates of the coefficients of the attributes and variables are shown in Table 2.

Table 2. Modeling Results

	Christchurch				**Hamilton**			
	MNL		**ML**		**MNL**		**ML**	
Attributes	**Coeff.**	**S.E**	**Coeff.**	**S.E**	**Coeff.**	**S.E**	**Coeff.**	**S.E**
Random parameters in utility functions								
COST	-1.243***	0.321	-1.311***	0.443	-1.790***	0.250	-1.966***	0.352
Nonrandom parameters in utility functions								
ACCESSIBILITY	-0.086**	0.040	-0.038	0.350	-0.091***	0.031	-0.083**	0.036
AVAILABILITY	0.107***	0.040	0.135***	0.046	0.086***	0.031	0.103***	0.036
ASC_T (Td-Bicycle)	0.439	0.281	-0.038	0.350	1.178***	0.240	2.320***	0.310
ASC_E (E-Bicycle)	0.992***	0.302	0.362	0.372	2.128***	0.255	3.192***	0.325
AGE	-0.051	0.047	-0.149**	0.060	-0.220***	0.043	-0.317***	0.057
GENDER	0.101*	0.056	0.092	0.073	-0.251***	0.048	-0.304***	0.066
MARRIAGE	-0.074**	0.035	-0.013	0.046	0.006	0.029	-0.038	0.037
TRIP_PURPOSE	-0.128***	0.036	-0.038	0.049	-0.086**	0.035	-0.097**	0.046
INCOME	0.015	0.043	0.105*	0.058	-0.130***	0.039	-0.255***	0.055
MODE	0.096*	0.055	0.257***	0.072	0.103*	0.062	0.034	0.077
Derived standard deviations of random parameter distributions								
COST			8.140***	0.523			7.792***	0.394
Model Statistics								
Log-Likelihood	-1568.64		-1342.67		-2405.10		-2074.81	
Pseudo- R^2	0.0172		0.1640		0.0355		0.1911	
AIC/N	2.161		1.853		2.069		1.787	
Observations	1472		1472		2408		2408	

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Economic theory provides some guidance in terms of the expected signs of several of the coefficients, and it can be seen that most of the coefficients of the generic attributes have the expected sign, and are statistically significant except for Accessibility for Christchurch in the ML model. The coefficients of the cost and accessibility variables are negative, indicating that alternatives with higher cost or longer walking distance are less likely to be chosen. In other words, higher costs or longer walking distance reduce the utility of alternatives. The coefficients of the Availability variables are positive, as expected, as respondents are expected to favor choosing modes with higher bicycle availability. This also implies that more bicycles and docking stations have positive effects on the utility of alternatives. In the ML model, the standard deviation of parameter distribution relates to the amount of dispersion that exists around the sample population. Therefore, statistically significant parameter estimates for standard deviations of random parameters, service cost, suggest the existence of heterogeneity in respondents' preference for these attributes.

All the alternative specific constants (ASC) are statistically significant for Hamilton but not statistically significant for ASC_E (E-bicycle) in the ML model, and both MNL and ML models for ASC_T (traditional-bicycle). The positive signs and statistically significant ASC for ASC_E (E-bicycle) indicate that, other things being equal, a bus with E-bicycle option is more attractive than a bus with walk option in both Christchurch and Hamilton. The ASC values for traditional bicycle are not statistically significant determinants of mode choice in Christchurch. However, when the socioeconomic terms in the model are removed, the ASC for traditional bicycle option for both models and also E-bicycle option for the ML model becomes statistically significant. In terms of socioeconomic characteristics, in general, the aged respondents, female, non-work-based trip respondents, and higher-income respondents may not receive benefits in Hamilton. The positive sign of MODE attribute shows the gain of benefit for the respondents walk to visit CBD in both cities.

Regarding the relative merits of the MNL and ML models, the model statistics indicate that the ML model yields a better model fit than the MNL model. The model shows substantial differences in the values of the AIC, the log-likelihood and the McFadden Pseudo-R^2 between the ML and MNL models, with the former having distinctly better values of the statistics.

The model has mode-specific attributes (SQ: Bus + Walk, Option 1: Bus + Traditional bicycle, Option 2: Bus + E-bicycle). Therefore, the cross-elasticities reflect the effect of percentage variations in the attributes of the existing option (SQ), a bus with traditional bicycle or E-bicycle on the mode share. Table 3 presents the mode choice cross-elasticities estimates based on the ML model. The results show that the probability of choosing Option 1 (Bus with traditional bicycle) is more sensitive to the changes in cost than the probabilities of choosing SQ and Option 2 (Bus with E-bicycle). The estimated elasticities in Table 3 indicate that if SQ costs increase by 1%, the probability of demanding SQ goes down by 5.672% for Christchurch and 6.465% for Hamilton respectively. According to the cross-elasticities, a 1% increase in SQ costs would imply increasing the probability of selecting Option 1 (Bus with traditional bicycle) by 5.06% and Option 2 (Bus with E-bicycle) by 0.757% for Christchurch.

Table 3. Elasticities of Cost

	Mode Share (%)	**SQ**	**Traditional Bicycle**	**E-Bicycle**
Christchurch	SQ	-5.672	4.472	0.650
	Traditional bicycle	5.060	-2.249	-1.047
	E-bicycle	0.757	-2.330	0.293
	Mode Share (%)	**SQ**	**Traditional Bicycle**	**E-bicycle**
Hamilton	SQ	-6.465	4.363	1.250
	Traditional bicycle	5.158	-3.700	-0.184
	E-bicycle	1.598	-0.876	-1.261

6. DISCUSSION AND CONCLUSION

This study aims to develop the idea of implementing PBSS(Public Bicycle Share Schemes) in the CBD(Central Business District)s of two medium-sized cities in NZ and to evaluate whether it is a viable transport option in addition to the urban transport network. This was conducted to promote healthier and better communities as well as reduce traffic congestion in an urban area. The study was initiated with prioritization of the type and location of a public bicycle sharing system in the existing CBDs, which alters major and current urban transport issues. The concern of CBD traffic problems gained a majority among the others. The literature on these urban problems in other, similar-sized cities, which have established a PBSS to change CBD users' travel behavior was reviewed. The literature review showed new aspects of the urban transportation network and explained the need for some particular changes in sustainable transport for livable urban life. The different forms of transport modes and urban planning were gathered from looking at the change made in many cities. Such studies, despite their importance, are relatively scarce due to issues related to data collection and confidentiality of personal information of potential participants. To achieve the objective, the study uses the Logistic Regression modeling, which postulates that CBD patrons' travel behavior depends on two components: 1) some observable attributes, such as walking distance, service fares, and bicycle availability; and 2) unobserved heterogeneity such as gender, income, and education. The latter is taken into account by characteristics of respondents such as gender, income, education, and use of mode to travel. In this study, multinomial logit and mixed logit models were used to determine the best model specification, and subsequently, to test the mode choice cross-elasticities for promoting greater use of the bicycle sharing system and public transport. The results of the modeling allow policymakers to design more appropriate strategies and policies for different segments of the population to improve an urban CBD. Furthermore, the modeling results indicate that in order to promote sustainable mobility in developing urban CBD, one policy would be to increase the connectivity of public transport services.

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