WHY INDIVIDUALS CHOOSE DOCKLESS BICYCLE-SHARING SERVICES? ASSESSING THE EFFECTS OF BUILT ENVIRONMENT AND LAND USE ATTRIBUTES[1]

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Introduction

Bike sharing has received immense popularity in many countries in the recent years. Bike sharing benefits its users through facilitating increased physical exercise, reduced emissions, increased accessibility, abated congestion, and addressing the first and last mile problem of public transit; overall ensuring a healthier living environment (Tran et al., 2015). One of the emerging bike sharing system is dockless – a bike sharing system that is station-less. In such systems, users have the flexibility to drop-off a bike for the subsequent use at any location within the designated territory (City of Kelowna, 2018). One of the advantages is that users are not required to search for stations or vacant docks to return their bikes. To ensure the successful operation of this active and shared mobility service, it is important to understand why individuals choose bicycle-sharing over other modes of transportation. This study investigates individuals' reasons for choosing Dockless bikeshare (DBS) over other modes. A latent segmentation-based logit (LSL) model is developed, utilizing DBS user survey data from Kelowna, BC. The LSL model is developed to capture unobserved heterogeneity among the users. This paper examines the influence of socio-demographic characteristics, travel attributes, built-environment attributes, and land use characteristics.

Literature review

Bike sharing system has experienced significant growth and evolution around the world – from the first generation pioneered by the Netherlands in 1960's to the fourth generation of dockless bike sharing (DBS) systems initiated in China in 2015 (Shi et al. 2018, Guo et al. 2017). DBS systems have emerged from the need to reduce the number of docking stations and associated facilities occupying public space and subsequently causing road congestion. Although DBS promises to revolutionalize the conventional bike sharing market, limited studies have focused on analyzing the DBS user behaviour. Majority of the existing studies have emphasized on modelling the user behaviour of traditional bike sharing systems (Bachand-Marleau et al. 2012). Among the few studies on DBS, Shi et al. (2018) employed a social network analysis method to understand the primary challenges with DBS and identify counter-measures; particularly focusing on the DBS sustainability from a network perspective. They identified several stakeholder-associated factors, such as sharing transport schemes and product lifecycle management, among others. Shen et al. (2018) explored the spatiotemporal patterns of dockless bike sharing usage in Singapore. They developed a spatial autoregressive model utilizing GPS data. There exist a research gap in examinig the user behaviour of DBS. More importantly, it is imperative to understand why people prefer to choose DBS over other modes, which is critical for ensuring the sustainability of DBS systems. This study contributes to the existing literature by investigating the factors affecting the reasons for choosing DBS over other modes. A latent segmentation-based logit model is developed to capture unobserved heterogeneity among the DBS users. The model extensively tests the effects of socio-demographics, built-environment, and land use characteristics.

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Data

The primary data source for this study is a survey conducted on the dockless bike share service users in Kelowna, British Columbia in 2018. Dropbike in association with the City of Kelowna is operating this service. Eliminating the missing data, the final sample includes complete response from a total of 282 users. Respondents were asked to identify their primary reason for choosing the bike sharing service. Besides, the survey collected information regarding respondents' socio-demographics (i.e. age, gender, and income), travel characteristics (i.e. personal vehicle or bicycle ownership, bicycle riding and dropbike usage frequency), and attitudinal statements (i.e. whether people agree that dropbike app is easy and reliable for renting bikes), among others. Among the secondary data sources, neighborhood attributes, built-environment characteristics, and land use information are collected from Open data portal of the City of Kelowna, MapCruzin.com, Statistics Canada, and Desktop Mapping Technologies Inc. (DMTI). The land use and built environment information are generated by creating a 1km buffer from the respondents' home location, which includes: number of the transit stop and activity points; length of the sidewalk, shared-pathway, bike-lane and cycle-track; and area of parking restraint, among. Population and dwelling density information are generated for the respondents' home dissemination area. In addition, road network-based distance from home to the nearest transit stop and activity points, and distance from home to the Central Business District (CBD) and shopping centre are determined.

Methodology and model building

This paper investigates individuals' reasons for choosing dockless bike sharing (DBS) service. The reasons are classified into the following six categories: fastest option (17.1%), cheapest option (19.5%), exercise purposes (7.3%), recreational purposes (40.7%), due to difficulties in finding parking space at destination (6.2%), and unavailability of other modes such as car and transit (9.2%). A latent segmentation-based logit (LSL) model is developed to capture unobserved heterogeneity among the users (Fatmi et al. 2017, Greene and Hensher 2003). According to the LSL model formulation, the probability for choosing DBS for an alternative reason j by individual user i is: $P_{ij}(i \in s) = \frac{e^{X_{ij}\beta_i}}{\sum_{j=1}^{J} e^{X_{ij}\beta_i}}$. Here, β is segment-specific parameter vector, X is built environment and land use attributes, and s is latent segments. Individuals are allocated into the s latent segment on the basis of the following segment allocation model: $\delta_{is} = \frac{e^{\alpha_s + \gamma_s y_i}}{\sum_{s=1}^{S} e^{\alpha_s + \gamma_s y_i}}$. Here, γ is segment-specific parameter vector, y is individual users' socio-demographic and travel characteristics, and α is constant.

Analysis results and discussion

For comparison purposes, this study develops a multinomial logit model (MNL) in addition to the LSL model. The LSL model outperforms the MNL model with a higher adjusted pseudo r-squared value (0.231). The final selected LSL model is estimated for 2 latent segments, which is determined on the basis of the Akaike information criterion (881.2). The latent segment allocation model retains the effects of following socio-demographics and travel attributes: age, income, and frequency of bike riding. The model results suggest that individuals aged 35-54 years show a higher probability to be included in segment 1. Furthermore, individuals with annual income more than $150,000 show a negative sign in segment 1. Therefore, segment 1 can be defined as a segment that includes mid-aged low-income frequent bike riders. On the other hand, segment 2 can be identified to include high-income non-frequent bike rider who are young or older. The model results are shown in Table 1.

The parameter estimation results of the LSL and MNL models are presented in Table-2. For the reason fastest mode, sidewalk length shows a positive relationship in segment 1. This implies that mid-age frequent bicycle users tend to choose dropbike as the fastest mode. On the other hand, in segment 2, a negative sign implies that higher income non-frequent riders might not choose dropbike for being the fastest mode. The closer the activity points from home, the more people will choose dropbike as the

Table 1. Latent Segment Allocation Model Results

Variables	Segment 1		Segment 2	
	Coefficient	t-stat	Coefficient	t-stat
Age 35 to 54	0.87	+2.03	reference	reference
Income less than 30,000 CAD $ per year	1.97	+3.05	reference	reference
Income greater than 1,50,000 CAD $ per year	-1.27	-2.02	reference	reference
Bike riding frequency 3-20 times in last 3 months	0.58	+1.49	reference	reference

Table 2. Parameter Estimation Results of the LSL Model

Variable Name	MNL		LCM			
			Class 1		Class 2	
	Co-eff.	t-stat	Co-eff.	t-stat	Co-eff.	t-stat
Fastest option						
Length of sidewalk in km	0.033	1.92	0.175	2.56	-0.091	-1.34
No. of Govt. and public services	0.009	0.21	0.396	2.40	-1.583	-3.55
Nearest activity point in m	0.46×10^{-4}	0.09	-0.004	-1.13	-0.001	-1.19
Dropbike riding frequency 3-20 times in last 3 months	0.844	2.13	1.01	1.70	2.140	2.04
Cheapest option						
Length of the shared pathway in km	0.294	2.65	0.426	2.57	1.037	1.57
No. of the transit stop	0.034	3.01	0.068	3.84	0.170	1.66
Length of bike-lane in km	0.059	1.37	0.139	2.42	-1.071	-2.08
Distance to CBD less than 1 km	-0.669	-1.31	3.382	2.62	-15.228	-2.86
Exercise purposes						
Gender (Female)	0.514	1.08	0.992	1.36	0.286	0.28
Length of sidewalk in km	0.033	1.73	0.095	3.29	0.222	1.96
Recreational purposes						
No. of food/leisure/lodging/parking activity points	-0.005	-0.19	0.268	3.25	-0.328	-1.15
Length of the shared pathway in km	0.154	1.61	0.337	2.29	-2.378	-2.71
Renting is easy via dropbike app and introduction of electric-assist bikes	0.041	0.20	-0.240	-0.88	3.111	1.97
Due to difficulties in finding parking space						
No. of total activity points	0.019	-0.61	0.764	1.24	-.801	-3.6
Alternate mode to dropbike-drive	0.606	1.16	1.705	1.52	0.965	0.9
Area of residential zones affected by timed parking restrictions in km	0.321	0.76	-2.322	-1.81	1.974	1.91
Unavailability of other modes such as car/transit						
No personal vehicle access	1.31	2.16	2.542	2.76	3.618	0.84
Length of bike-lane and cycle-track in km	0.093	1.95	0.201	2.91	-0.517	-0.67
Walking distance to get a dropbike greater than 20 min	-0.939	-0.87	-1.390	-1.14	-1.390	-1.14

fastest mode. A shared-use pathway may be paved or unpaved defined as a form of infrastructure that is shared by both pedestrians and bicyclists. The higher the number of transit stops within 1 km from the users' home, the higher the probability for choosing dropbike as the cheapest option. Interestingly, low-income individuals in segment 1 are found to be more sensitive than high-income groups in segment 2. This might imply that accessible transit option encourages low-income people to use dropbike more. Similarly, shared pathway shows a positive relation in both the segments. The length of bike-lane exhibits a positive relationship in segment 1. On the contrary, bike-lane and distance to CBD less than 1 km do not affect dropbike usage as a cheap mode for high-income individuals in segment 2.

In the case choosing for exercise purposes, females are found to be more likely to use, which might reflect that females are more health conscious than their male counterpart. The more the sidewalk length, the more people will choose dropbike for exercise purposes. The number of food/leisure/lodging/parking activity points positively influence the choice of dropbike for recreation purposes in segment 1. Nevertheless, in segment 2, a negative relationship is found. Length of the shared pathway increases the probability of choosing dropbike in segment 1. Furthermore, what we found is less than frequent bike riders are less likely to prefer dropbike for recreational purposes, if they have to share path with pedestrians. If dropbike renting app works reliably and electric-assist bikes are initiated, there will be a high possibility that non-frequent riders will use it more for recreational purposes. In the case of parking unavailability, dropbike is found to replace driving. Areas with higher number of activity locations are expected to induce parking constraint, hence might trigger a higher use of dropbike. In the case of unavailability of other modes, specifically, individuals without personal vehicles shows a greater likelihood to use dropbike. Bike infrastructure (i.e. bike-lane and cycle track) attract frequent bike riders more to choose drop bike when another travel mode is unavailable.

Concluding remarks

This study contributes by developing a latent segmentation-based logit (LSL) model to investigate the reason behind choosing dropbike over other modes. The study extensively tests the influence of socio-demographic characteristics, built environment attributes, and land use attributes. The model results suggest that significant heterogeneity exists between the two latent segments, which are identified as mid-aged low-income frequent bike users' segment and high-income less frequent younger and older riders. The results reveal that built environment attributes such as length of sidewalk, bike lane, and shared pathway; and land use characteristics such as distance to CBD and density of activity points significantly influence the reason for choosing dockless bike sharing services. In summary, the findings of this study provide important behavioral insights, which will assist the decision-makers in developing effective policies to promote and improve the efficiency of the dockless bike sharing systems.

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