Why Individuals Choose Dockless Bicycle-sharing Services?

Assessing the Effects of Built Environment and Land Use Attributes

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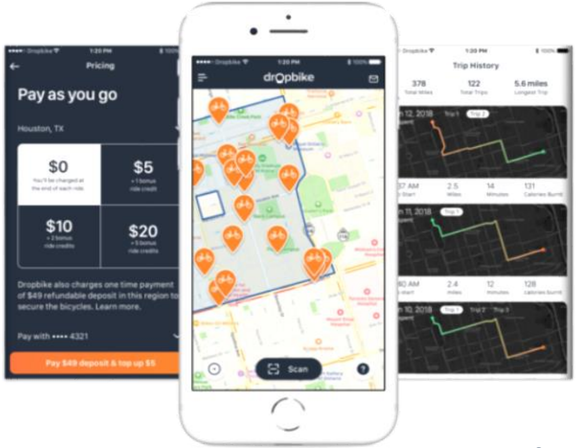
OUTLINE

- Background
- Objectives
- Data Sources
- Methodology
- Model Results
- Summary of Contributions and Future Work

WHAT IS DOCKLESS BIKE SHARE (DBS)?

- Dockless bike share (DBS) system is a station-less service
- Emerged to reduce the need for docking stations and associated facilities occupying public space
- Scan, ride, and park at anywhere
- DBS system have been introduced in 200 cities all over the world
- Ofo , Mobike, Dropbike, and Jump among others are the popular bike share companies



DOCKLESS BIKE SHARE (DBS) IN KELOWNA

- City of Kelowna – 18 month pilot project started July 2018
- Dropbike - a Canadian based dockless bikeshare company
- GPS device are located within the dropbikes to locate bikes and prevent theft
- Havens - are designated locations for bicycle parking
- To encourage parking at havens, bikeshare users who ended trip inside of havens were credited

DOCKLESS BIKE SHARE USAGE IN KELOWNA (CNTD.)

User Behaviour of Dockless Bikesharing Services?

Figure: Haven Locations in Kelowna

Figure: Trip Origins in Kelowna

LITERATURE REVIEW

Aspects	Studies	Gaps
Focus of study	▪ Emphasized on modelling the user behaviour of traditional bike sharing systems (Bachand-Marleau et al. 2012, Guo et al. 2017). ▪ Investigation of spatiotemporal patterns of dockless bike sharing usage in Singapore (Shen et al. 2018).	Limited studies have focused on analyzing the DBS users' behavior.
Method	▪ Binary logistic and linear regression models (Bachand-Marleau et al. 2012), social network analysis method (Shi et al. 2018), spatial autoregressive model (Shen et al. 2018).	Failed to capture the unobserved heterogeneity across the users.
Influential factors	▪ Primary challenges with DBS focusing on the DBS sustainability from a network perspective (Shi et al. 2018). ▪ Socio-demographics and travel characteristics (Bachand-Marleau et al. 2012). ▪ Influence of bike fleet size, surrounding built environment, access to public transport, bike infrastructure, and weather conditions (Shen et al. 2018).	Important to understand the effects of built environment attributes.

OBJECTIVES

- To investigate the user behaviour of dockless bikesharing services.
- To develop a latent segmentation-based logit (LSL) model that captures unobserved heterogeneity among the DBS users.
- To test the effects of built-environment and land use characteristics.

DATA SOURCES

- Data collected through a survey conducted on Dropbike users by the City of Kelowna
- Survey data include socio-demographic, travel characteristics, and attitudinal references/statements
- Sample size - 282

Socio-demographic	Travel characteristics	Attitudinal statements
• Age • Gender • Income • Location	• Vehicle ownership • Bicycle ownership • Frequency of bike use • Alternative mode to bikesharing • Primary reason for choosing bikesharing	• Reduce emissions • Reduce congestions • Made commuting easier • Bicycles are often parked in my way

- ✓ Cheapest mode
- ✓ Fastest option
- ✓ Exercise purpose
- ✓ Recreation/fun purpose
- ✓ Difficulty in finding parking space
- ✓ Unavailability of other modes and other reasons

DATA SOURCES

- Built Environment and Land-use data
  - Bicycle infrastructure
    - ✓ Shared pathway
    - ✓ Bike lane
    - ✓ Cycle track
  - Location of transit stop
  - Location of CBD
  - Land use information
- Neighbourhood Characteristics
  - Population density
  - Employment density

DATA ANALYSIS

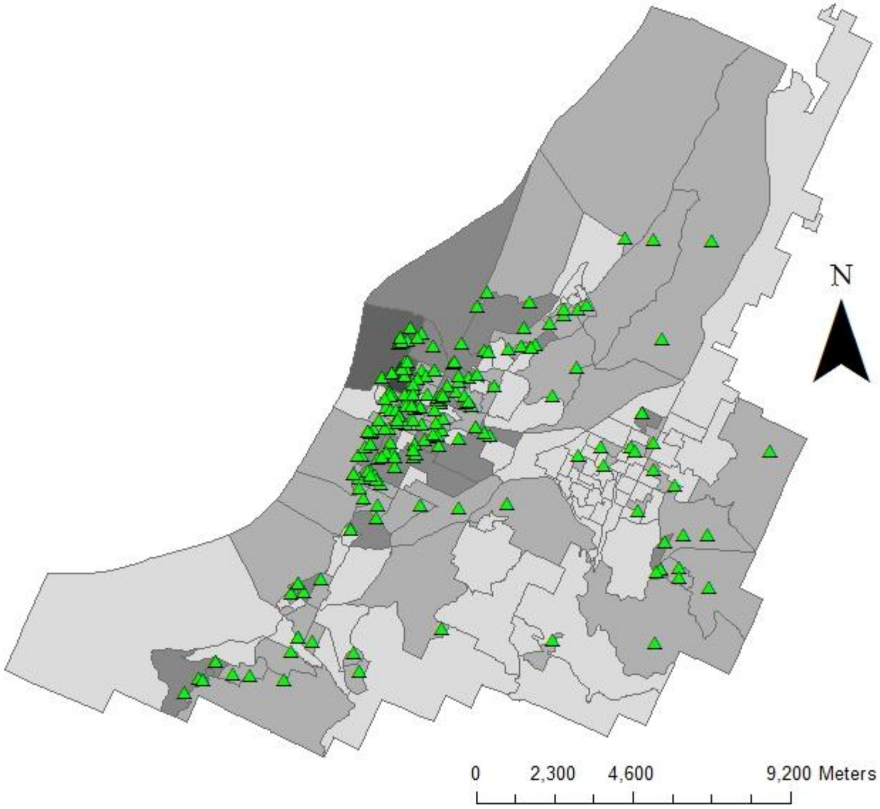
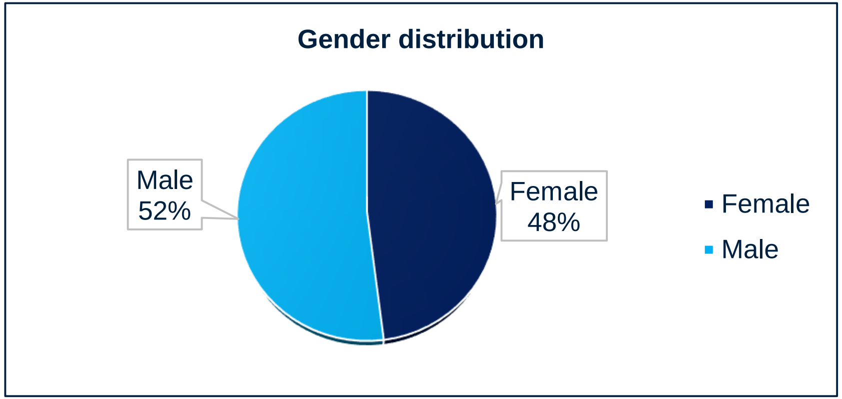
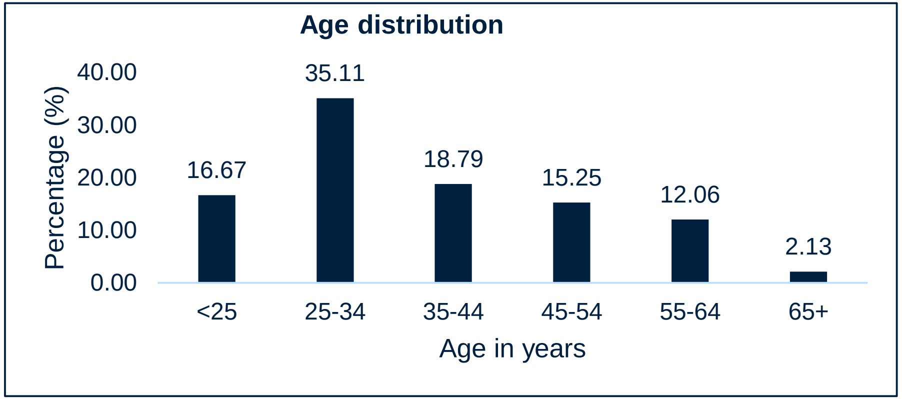
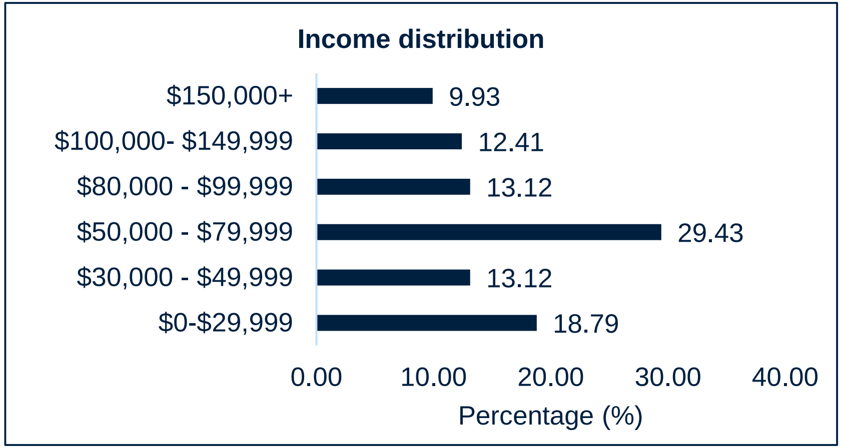


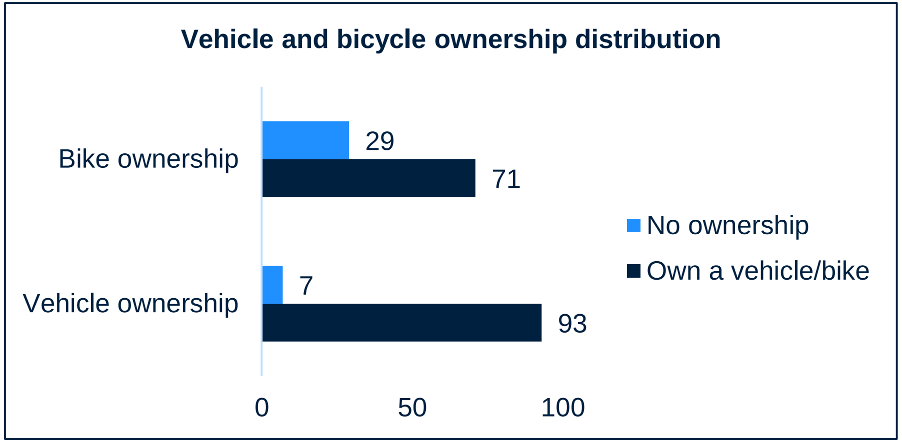
Figure: Dropbike users' home locations in Kelowna

DATA ANALYSIS (CNTD.)

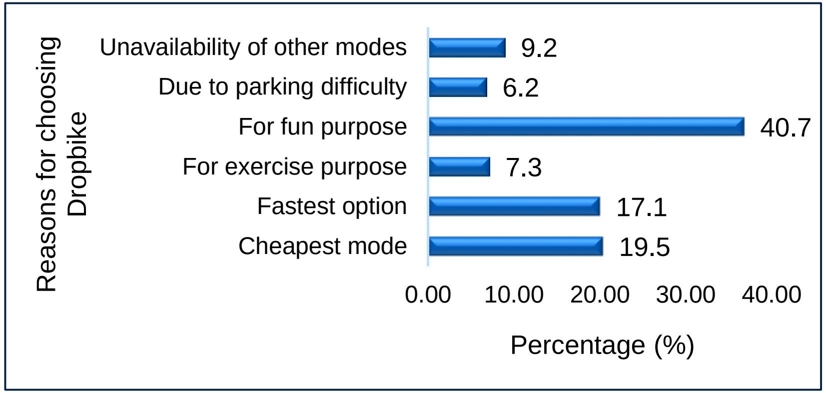




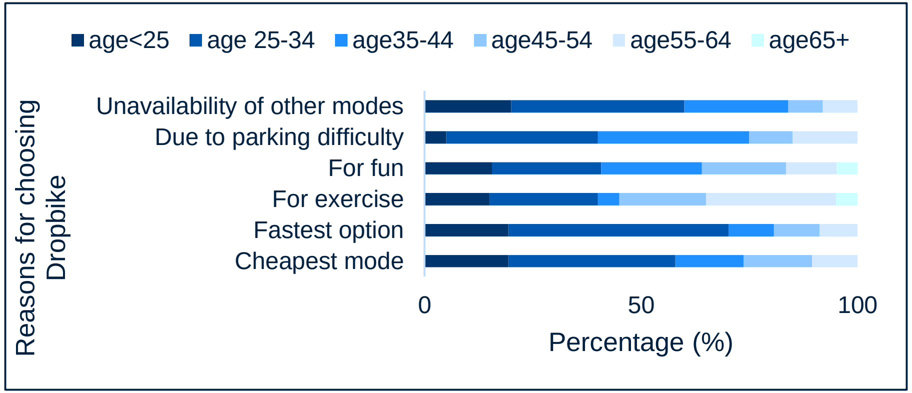




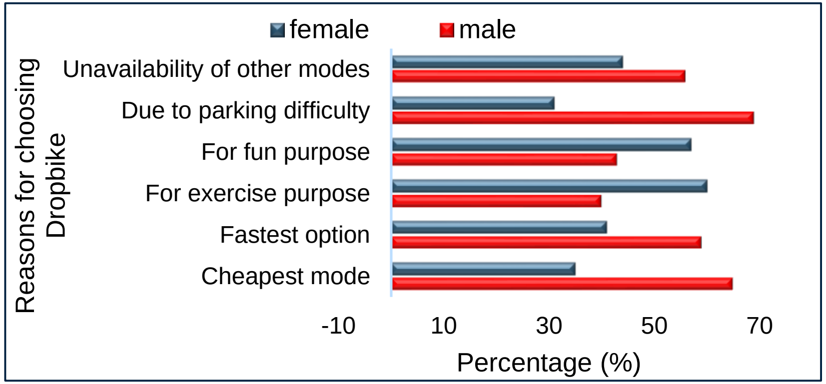
DATA ANALYSIS (CNTD.)



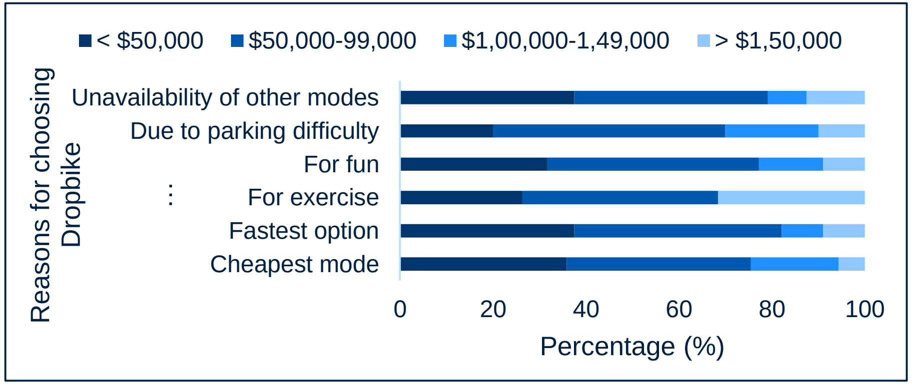
Distribution of Reasons for Choosing Dropbike



Age Distribution



Gender Distribution



Income Distribution

METHODOLOGY

- **Latent Segmentation-based Logit (LSL) Model**

  - Choice Probability

$$P_{ij}(i \in s) = \frac{e^{a_s + X_{ijt}\beta_s}}{\sum_{s=1}^{S} e^{a_s + X_{ijt}\beta_s}}$$

  - Latent Segment Allocation Component

$$\Phi_{is} = \frac{e^{\omega_s + \theta_s Z_i}}{\sum_{s=1}^{S} e^{\omega_s + \theta_s Z_i}}$$

- Maximum Likelihood Function

$$LL_{\max} = \sum_{n=1}^{N} \ln\left[\phi_{is} P_{ij}(i \in s)\right]^{\gamma_{ij}} = \sum_{n=1}^{N} \ln\left[\sum_{s=1}^{S}\left(\frac{e^{\omega_s + \theta_s Z_i}}{\sum_{s=1}^{S} e^{\omega_s + \theta_s Z_i}}\right)\left(\frac{e^{a_s + X_{ijt}\beta_s}}{\sum_{s=1}^{S} e^{a_s + X_{ijt}\beta_s}}\right)\right]^{\gamma_{ij}}$$

- Estimates:

β = segment specific parameter for s segments

θ = segment membership parameter for $s-1$ segments

Here,

i = individual

s = latent segment

z = observed attributes

ω = segment membership constant

θ = segment membership parameter vector

j = alternative reasons for choosing DBS

β = segment specific vector parameter

MODEL RESULTS

Goodness of Fit Measures:

Criteria	LSL Model	
	Segments: 2	**Segments: 3**
Log-likelihood (at convergence)	-388.60	-386.078
BIC	3.182	3.352
AIC	3.125	3.277

MODEL RESULTS

Goodness of Fit Measures:

Criteria	MNL Model	LSL Model (2 segments)
Log-likelihood	-428.548	-388.597
Adjusted Pseudo R-squared	0.0165	0.231
AIC	3.210	3.125
BIC	3.211	3.182

MODEL RESULTS (contd.)

Segment Allocation Result :

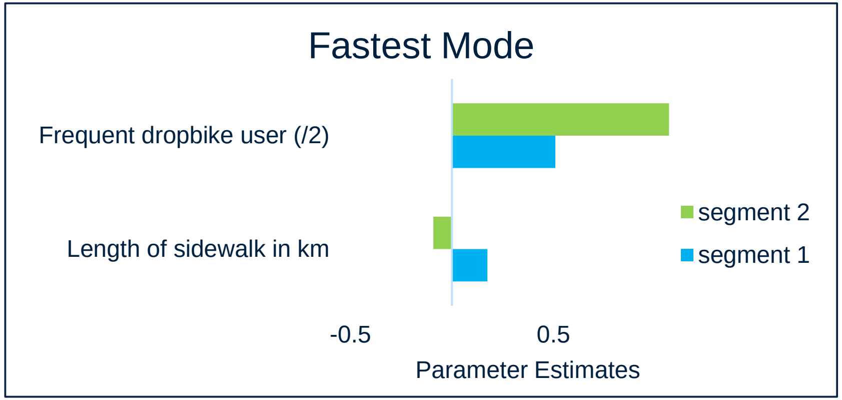
Variables	Segment 1		Segment 2
	Coefficient	t-stat	Coefficient (t-stat)
Age 35 to 54 years	0.87	+2.03	Reference
Income less than 30,000 CAD $ per year	1.97	+3.05	
Income greater than 1,50,000 CAD $ per year	-1.27	-2.02	
Frequent bike user	0.58	+1.49	

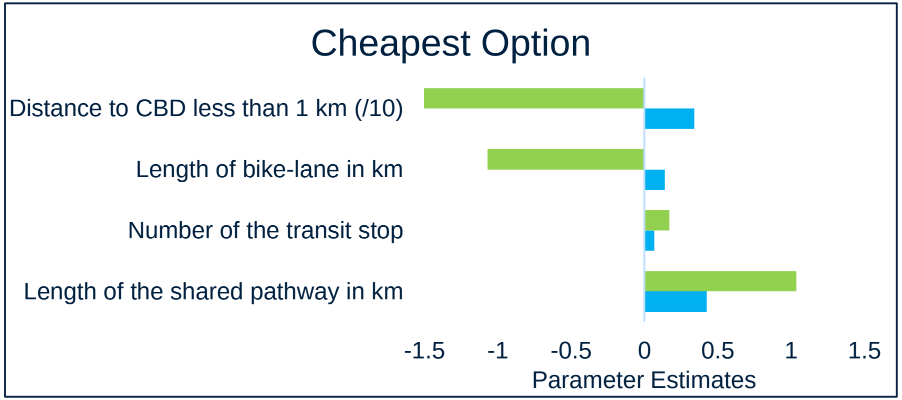
Segment 1: Mid-age, low income, and frequent bike user
Segment 2: Younger and older, high income, and non-frequent bike user

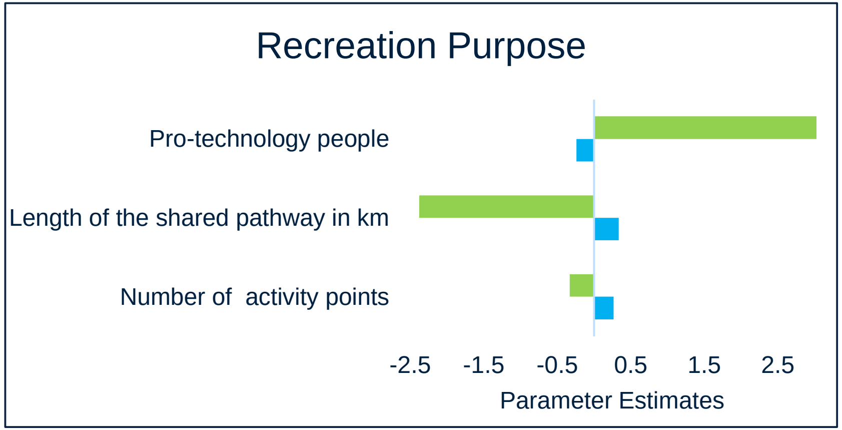
MODEL RESULTS (contd.)

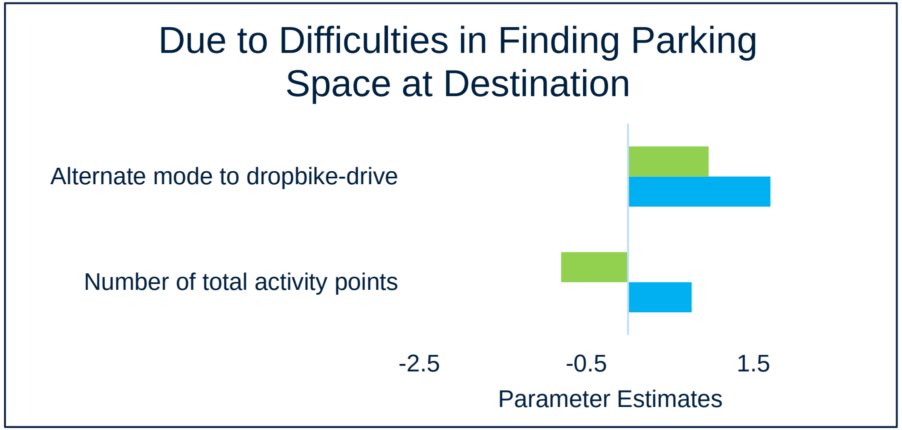
Variables	LSL Model Segment 1		LSL Model Segment 2	
	Coefficient	t-stat	Coefficient	t-stat
Cheapest option				
Length of the shared pathway in km	0.426	2.57	1.037	1.57
Number of the transit stop	0.068	3.84	0.170	1.66
Length of bike-lane in km	0.139	2.42	-1.071	-2.08
Distance to CBD less than 1 km	3.382	2.62	-15.228	-2.86
Fastest option				
Length of sidewalk in km	0.175	2.56	-0.091	-1.34
Number of Govt. and public services	0.396	2.40	-1.583	-3.55
Nearest activity point in m	-0.004	-1.13	-0.001	-1.19
Dropbike riding frequency 3-20 times in last 3 months	1.01	1.70	2.140	2.04
Exercise purposes				
Gender (Female)	0.992	1.36	0.286	0.28
Length of sidewalk in km	0.095	3.29	0.222	1.96
Recreational purposes				
Number of food/leisure/lodging/parking activity points	0.268	3.25	-0.328	-1.15
Length of the shared pathway in km	0.337	2.29	-2.378	-2.71
Renting is easy via dropbike app	-0.240	-0.88	3.111	1.97
Due to difficulties in finding parking space				
Number of total activity points	0.764	1.24	-.801	-3.6
Alternate mode to dropbike-drive	1.705	1.52	0.965	0.9
Area of residential zones affected by timed parking restrictions in km	-2.322	-1.81	1.974	1.91
Unavailability of other modes such as car/transit				
No personal vehicle access	2.542	2.76	3.618	0.84
Length of bike-lane and cycle-track in km	0.201	2.91	-0.517	-0.67
Walking distance to get a dropbike greater than 20 min	-1.390	-1.14	-1.390	-1.14

KEY FINDINGS









CONCLUSION

- Summary of Contributions
  - Investigates the user behaviour of dockless bikesharing services
  - Develops a latent segmentation-based logit (LSL) model
  - Model confirms that unobserved heterogeneity exists among the users
  - Built environment attributes and travel characteristics are found to be significant determinants
- Future Research
  - Continue testing land use and neighbourhood characteristics
  - Testing elasticity effects

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Thank You
Questions?

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