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Developing vehicular and non-vehicular trip generation models for mid-rise residential buildings in Kelowna, British Columbia: Assessing the impact of built environment, land use, and neighborhood characteristics

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Abstract: This study develops vehicular and non-vehicular trip generation models for mid-rise, multi-family residential developments. A comparative analysis of observed and Instiutue of Transportation Engineers (ITE) trip rates suggests that ITE rates consistently overestimate. A latent segmentation-based negative binomial (LSNB) model is developed to improve the methodology for estimating vehicular and non-vehicular trips. One of the key features of an LSNB model is to capture heterogeneity. Segment allocation results for the vehicular and non-vehicular models suggest that one segment includes suburban developments, whereas the other includes urban developments. Results reveal that a higher number of dwelling units is likely to be associated with increased vehicle trips. For non-vehicular trips, a higher number of dwelling units and increased recreational opportunities are more likely to increase trip generation. The LSNB model confirms the existence of significant heterogeneity. For instance, higher land-use mix has a higher probability to deter vehicular trips in urban areas, whereas trips in the suburban areas are likely to continue increasing. Higher density of bus routes and sidewalks are likely to be associated with increased non-vehicular trips in urban areas, yet such trips are likely to decrease in suburban areas. An interesting finding is that higher bikeability in suburban areas is more likely to increase non-vehicular trips. The findings of this study are expected to assist engineers and planners to predict vehicular and non-vehicular trips with higher accuracy.

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1 Introduction

Transportation impact assessment (TIA) is an important tool and requirement to analyze the impact of any proposed development on the transportation network. The most commonly referenced guideline for TIAs is the Trip Generation Handbook, which is developed by the Institute of Transportation Engineers (ITE) (Institute of Transportation Engineers, 2017). This manual includes trip generation data plots for various land-use descriptions, time periods, settings or location, and trip types (i.e., vehicle or

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person). This handbook provides trip generation rates for ten broad land-use categories such as industrial, residential, recreational, and retail among others. The urban settings include center city core, dense multi-use urban, general urban/suburban, and rural. Trip rates are provided in relation to explanatory variables such as the size of the land development (e.g., dwelling type, or floor space). One of the limitations of the ITE older version recommended trip rates is that it does not account the effects of built environment attributes, such as transit infrastructures, mixed land uses, and walk and bike infrastructures, among others (Shafizadeh et al., 2012). The major reason for this incapacity is that the data collection for ITE guidelines started in the 1960s when the transportation network was designed for vehicular trips. As a result, the data predominantly represents vehicle trips in the suburban areas of the United States. In the context of the present era, transportation and urban configurations have significantly evolved since the 1960s (Clifton et al., 2015). Consequently, in the 10th edition, ITE modified the database significantly and eliminated all the data prior to 1980. However, Government agencies around the world are investing to promote sustainable travel options, such as walking, biking, and transit, among others (City of Kelowna, 2019). Although ITE trip generation manual 10th edition includes the total person trip generation rates (Institute of Transportation Engineers, 2017), it does not provide the multi-modal trip generation guideline. Therefore, the ITE trip rate might provide an overestimation of vehicle trips, since people have reduced their share of vehicle usage (Clifton et al., 2015). Nowadays, people are making more multimodal trips, which indicates the requirements of a trip generation guideline for alternative transportation modes. Interestingly, ITE recently introduced the estimation of trip generation by passenger vehicle, walk, transit, bike, and truck for varying land-use characteristics and settings (Institute of Transportation Engineers, 2020). However, it is critical to incorporate the micro-level quantitative effects of both the attributes of the development and the surrounding built environment. Furthermore, heterogeneity in trip generation rates might exist among the developments (Ewing et al., 2015). For improved estimation of trip generation, advanced models are required to capture such heterogeneity across developments. Therefore, there exists a need for further research in developing advanced models for improved estimation of trip generation rates, including vehicular and non-vehicular trips.

This study investigates vehicular and non-vehicular trip generation for the mid-rise multi-family residential developments in Kelowna, which is located in the south of British Columbia. This research conducts a trip count survey for the mid-rise multi-family residential developments in Kelowna. This data is utilized to formulate a latent segmentation-based negative binomial (LSNB) model for vehicular and non-vehicular trips including walk, bike, and transit. One of the key features of this study is to capture unobserved heterogeneity across a range of urban land-use configurations. Such heterogeneity is captured by formulating a latent segment allocation model within the LSNB framework. Mid-rise multi-family developments are allocated into discrete latent segments. Another unique aspect of this study is to extensively test the impact of built environment attributes such as land use, transportation infrastructure, neighborhood, and accessibility measures.

2 Literature review

The Trip Generation Handbook developed by ITE has been widely used for traffic impact assessments (TIAs) of land developments. This initial guideline was developed using data mostly collected during the 1960s from the vehicle dominated suburban neighborhoods of the USA (Association of Bay Area Governments, 2008). During that era, private vehicle was the predominant mode of transportation; whereas, transit, walk, and bicycle facilities were very limited. Consequently, the ITE Trip Generation Handbook prior to the 10th edition provides only vehicle trip rates. One of the key changes since the 9th edition is the inclusion of both vehicle and person trip generation data for varying land-use settings.

This edition also added new data in the database. For example, sites were surveyed in the 1980s, the 1990s, the 2000s, and the 2010s in the USA and Canada for multifamily low-rise housing land characteristics. Vehicle trip rates are developed in relation to different attributes of the developments such as dwelling units or floor areas among others. In addition to the land development attributes, trip generation is significantly influenced by the built environment, the land use, accessibility, and neighborhood characteristics (Ewing et al., 2015). Therefore, the ITE recommended trip generation rates might provide inaccurate rates since it does not consider the micro-level quantitative effects of built environment, density, and multi-modal transportation systems that vary by the different land-use settings (Evans et al., 2003). For example, how the distance of transit stop or bicycle facility influence vehicular and non-vehicular trip generation within the urban/suburban setting. Although, ITE updated the latest edition with a supplement that provides the estimation of trip generation by passenger vehicle, walk, transit, bike, and truck for different land-use characteristics and settings (Institute of Transportation Engineers, 2020), it is difficult to predict the multi-modal trips precisely in an aggregate-level land-use setting. For example, distance to transit stops and number of transit routes within the neighborhood might influence the transit trips in an urban area. Walking trips might be stimulated by the increased land-use diversity, good sidewalk facility, and easier accessibility to transit (Ewing et al., 2015). Therefore, there is a need to evaluate the micro-level influence of the built environment, land use, accessibility, and neighborhood characteristics for vehicular and non-vehicular trips.

With the limitations of the ITE guidelines, transportation engineers and planners are challenged to accurately perform TIA studies. In such scenarios, ITE suggests developing local rates (Institute of Transportation Engineers, 2004). In this line of work, some local governments have adjusted the ITE rates for different urban contexts. For instance, the Virginia Department of Transportation utilizes a 10% reduction of the ITE rate for sites with frequent transit services (Virginia Department of Transportation, 2013). Gard (2007) proposed that a residential project of 200 single-detached residential units within 1.5 miles of an existing rail station would generate 8% to 10% fewer trips than the ITE rate. The Wisconsin Department of Transportation (Traffic Analysis & Design Inc., 2017) reported that ITE overestimates daily traffic by 28% on weekdays for mixed-use developments. They recommended adjustment of trip rates for several land-use types. For example, in the case of movie theaters they suggested a trip rate of 14.90 instead of the ITE rate of 20.22 for PM peak (Traffic Analysis & Design Inc., 2017). Moreover, the Transit Cooperative Research Program (TCRP) reported that ITE significantly overestimates vehicle trips for transit-oriented developments (TOD) in urban areas (Arrington & Cervero, 2008). Furthermore, Maryland State Highway Administration explored how senior housing and city center expansions impact nearby roadways and transit (Mansoureh & Ricardo, 2010). They found that the ITE manual underestimates the vehicle trips generated by age-restricted housing. In the case of town centers, actual trip rates also deviate from the ITE rates. Lapham (2001) investigated the trip generation and modal split in the Portland Metropolitan Region. It was found that the average trip generation rate for the eight TODs in Portland is significantly lower than the ITE rates. Moreover, Clifton et al. (2015) reported a comprehensive review of studies in the domain of trip generation from 1987 to 2011 and revealed a discrepancy between the actual and ITE trip rates over the years. The range of difference was found higher for trips generated in the central business district, downtown areas, and heterogeneous land-use zones. Schneider et al. (2013) collected multimodal trip generation data from the smart growth areas of California. They revealed that the ITE rates overestimate the actual rates by more than 2 times in suburban areas. In the case of smart growth projects, ITE guidelines lack precision due to the fact that the majority of the data was obtained at suburban locations. Handy et al. (2013) developed a method to estimate multi-modal trip generation rates for smart-growth land developments. They initially estimated the vehicular trips based on ITE rates. Then, they derived an adjustment factor based on the calculated smart-growth factor which is a function of site and adjacent land-use settings.

Therefore, it is evident that ITE guidelines have significant limitations in estimating vehicle trips with reasonable accuracy. Although several attempts have been made to adjust the ITE trip generation rates, limited studies have attempted to develop empirical procedures to improve the estimation methods, which might add further error to the rates (Clifton et al., 2015).

Some research efforts have been made to develop empirical models to adjust the ITE trip rates. For example, Clifton et al. (2015) developed regression models to adjust ITE rates for restaurants, convenience markets, and drinking places in Portland, Oregon. They developed nine models to test the impact of built environment attributes such as activity density, number of transit corridors, employment density, and intersection density among others. Furthermore, Gulden et al. (2013) utilized a mixed-use development (MXD) trip generation model to estimate car, walking, and transit trips for an MXD. They suggested several improvements such as applying modifications to the ITE rates and accounting for shorter vehicle trips in MXD areas, among others. Clifton and Currans (2019) investigated the trip generation for multi-family developments. They developed multivariate statistical methods to explore the factors affecting multi-modal trips. As discussed above, most of the previous researches have adjusted vehicular trip rates. Development of rates for multi-modal trips have not occurred to any significant extent.

Trip generation pattern for compact smart growth cities is driven by multi-modal trips. Multi-modal trips are significantly influenced by built environment attributes such as bicycle infrastructure, transit accessibility, sidewalks, land use, connectivity, household type, and employment density among others. For example, Currans et al. (2020) collected trip counts from affordable housing developments in Los Angeles and San Francisco and found associations of employment density, population density, and parking supply for vehicular and person trips. Tian et al. (2015) presented that the likelihood of trips generated in mixed-use development is influenced by jobs within the development, job-population balance, and intersection density among others. In another study, Ewing et al. (2015) tested several built environment attributes to forecast trip generation. They found a negative association of car trips with the increase of diversity of land use and density of activity points. On the other hand, they reported increased probability of walk trips with the increase of land-use index, activity density, and accessibility to employment by public transport. In the case of bicycle trips, they revealed the associations of intersection density, public transport stop density, and population among others. In another study, Targa & Clifton (2005) argued that walk trips are influenced by population density, street connectivity, public transport accessibility, park area, and diversity of land use among others. The impact of combined effects of the built environment, land development, and neighborhood characteristics on trip generation in multi-family developments has not been investigated to a significant extent.

Methodologically, most of the empirical studies regarding ITE trip adjustments have adopted a linear regression modeling technique (Clifton et al., 2015; Clifton & Currans, 2019). One of the major limitations of the linear regression models is the normal distribution of the error term. This limitation is tackled by the alternative formulation of Poisson regression (Comer et al., 2014) and negative binomial regression (Poch & Mannering, 1996) models. However, these traditional regression models do not account for heterogeneity. For example, whether the influence of weather, elevation, bike facilities, and traffic on the demand of bicycling varies across the skilled and experienced bicyclists or not (Motoaki & Daziano, 2015). Adverse weather conditions might discourage unskilled bicyclists from bicycling more strongly than that of skilled bicyclists. Thus, there might exist unobserved heterogeneity across the bicyclists. Such heterogeneity might present across the residential developments for multi-modal trip generation which needs to be captured in the modeling framework for better prediction. If heterogeneity exists among the sample data, biased estimation might result in poor and inconsistent predictions. To capture heterogeneity, traditional regression modeling techniques need to be extended to advanced models such as latent segmentation-based regression model (Garver et al., 2008) or random parameters regression model (Anastasopoulos & Mannering, 2009), among others. These models are capable of capturing heterogeneity by distributing parameters using a discrete distribution (Greene & Hensher, 2003) or a continuous distribution (Revelt & Train, 1998). Further research is required to develop improved empirical modeling techniques to address unobserved heterogeneity.

2.1 Contributions of the current study

The contributions of this study are three-fold: i) developing methods for estimating vehicular and non-vehicular trips, ii) formulating a latent segmentation-based negative binomial (LSNB) model, and iii) examining the combined effects of the size of the development and built environment attributes. This study develops trip generation models for vehicular trips and non-vehicular trips including walk, bike, and transit, among others. The models are developed for mid-rise multi-family residential developments. This study develops an advanced regression modeling technique, known as the latent segmentation-based negative binomial (LSNB) model. The purpose for developing the LSNB model is to capture unobserved heterogeneity in vehicular and non-vehicular trip generation across a wide range of urban context. Heterogeneity is captured by formulating a flexible latent segment allocation model within the LSNB framework. This segment allocation model distributes locations into discrete latent segments based on their observed attributes. Finally, this study contributes by testing the combined effects of the size of sites such as the number of dwelling units and built environment attributes such as land use, transportation infrastructure, neighborhood, and accessibility measures.

3 Methodology

This study develops an advanced regression model for estimating vehicular and non-vehicular trip generation from mid-rise multi-family developments. Specifically, a latent segmentation-based negative binomial (LSNB) model is developed that captures heterogeneity by assigning development sites into discrete latent segments. In the case of the count modeling approaches, Poisson and negative binomial models are commonly used (Tabeshian & Kattan, 2014). One of the assumptions of the Poisson regression model is that the mean of the dependent variable is equal to its variance (Ashqar et al., 2019; Chen et al., 2016). In this study, the means for both the vehicular and non-vehicular trips are not equal to their variances. Rather, the data is over-dispersed as the variances exceed the mean value for both vehicular and non-vehicular trips. To account for this over-dispersion attribute of the data, a negative binomial model is developed. Assuming that Yj is the pm peak hour trip (vehicular or non-vehicular) generated at the mid-rise multi-family developments j, which is allocated to segment s. The probability expression for the negative binomial model is as follows:

$$P_{js}\,[Y_j\,|s]) = \frac{\Gamma(Y_j + \lambda s^{-1})}{\Gamma(Y_j{+}1)\;\Gamma(\lambda_s{-}^{1})}\;\;(\frac{1}{1+\lambda_s\,\mu_{js}})^{\frac{1}{\lambda s}}\,(1 - \frac{1}{1+\lambda_s\,\mu_{js}})^{Yj}) \tag{1}$$

Here,

Γ(.)= Gamma function,

λ_s = negative binomial dispersion parameter specific to segment s (to be estimated)

μ_{js} = mean of vehicular or non-vehicular (depending on the model) trip generated during the pm peak hour from the mid-rise developments *j* which is assigned to segment *s*.

The Gamma distributed disturbance term of the negative binomial model relaxes the variance assumption of the Poisson regression model (Cai et al., 2016). The expression of μ_{js} takes the following form:

$$\mu_{js} = e^{\theta_s T_j} \tag{2}$$

Here,
θ_s = segment-specific coefficient of the parameter (to be estimated), and
T_j = observed attributes of the mid-rise buildings

Now, the allocation of mid-rise development j into segment s is determined by developing a flexible segment allocation component within the LSNB framework. This component is formulated to assign the sites into discrete latent segments based on the built environment attributes of the mid-rise residential developments j. This segment allocation model takes the form of the following standard logit model:

$$P_{js} = \frac{e^{\alpha_s + \beta_s X}}{\sum_{s=1}^{S} e^{\alpha_s + \beta_s X_s}} \tag{3}$$

Here,
X_s = observed attributes of the mid-rise developments
β_s = segment-membership coefficient of the parameter (to be estimated), and
α_s = segment-membership constant (to be estimated)

To identify the segment allocation model paraments, one of the latent segments is considered as the 'reference' segment by fixing the value of β_s and α_s as 'zero' (Khan et al., 2017).

The unconditional probability can be expressed as:

$$P_j(Y_j) = \sum_{s=1}^{S} (P_{js}[Y_j|s]) * P_{js} \tag{4}$$

The log-likelihood function can be expressed as:

$$LL = \sum_{s=1}^{N} \log\left(\sum_{s=1}^{S} (P_{js}[Y_j|s]\right) * P_{js} \tag{5}$$

Here, N is the total number of observations. The model estimates segment specific parameters θ_s for s segments, and segment membership parameters β_s and α_s for s-1 segments. These parameters are estimated using the maximum likelihood method. The goodness-of-fit measure of the model is evaluated using a log-likelihood function, Akaike Information Criteria (AIC), Bayesian Information Criteria (BIC), and adjusted pseudo rho-squared value (Orvin & Fatmi, 2020a).

4 Study area

The study area for this research is Kelowna, the largest city of Interior British Columbia (BC), shown in Figure 1. Kelowna is presently the fastest-growing city in British Columbia. Since 1981, the population in Kelowna has grown rapidly at an average annual growth rate of 2.22%. As of 2015, dwelling units in Kelowna rises to about 8% over a five-year period (City of Kelowna, 2018b). Rapid urban growth and high housing costs have triggered significant multi-family residential developments in the urban and suburban areas of Kelowna (City of Kelowna, 2018b). Although private vehicle is the predominant mode of transportation in Kelowna (City of Kelowna, 2018a); recently, the city has made significant investments in its transit, walk, and bike infrastructure (City of Kelowna, 2019). As a result, an increase in the share of alternative modes is observed (Acuere Consulting Inc., 2015). However, the industry practice is to use the ITE trip generation guideline for TIAs, which is expected to be over-estimating vehicle trips. The planners and engineers of the City of Kelowna are challenged to accurately predict the impacts of these developments on the transportation system. The need for adjusting the ITE has motivated this study to investigate trip generation rates for multi-family residential developments in Kelowna.

5 Data

5.1 Principal data source and data collection

The data for this study were collected from 81 locations in March of 2019 in Kelowna. The data collection focused on the mid-rise and high-rise multi-family residential developments. According to the ITE definition, a mid-rise development comprises apartments, townhouse, and condominiums located within the same building with at least three other dwelling units having three to ten floors, which is denoted in ITE manual with the land-use code (LUC) of 221. High-Rise development is apartments, townhouses, and condominiums that have more than ten floors as mentioned in the ITE LUC of 222 (Institute of Transportation Engineers, 2017). A total of 78 locations out of 81 were mid-rise buildings. This study is limited to mid-rise multi-family developments. The data collection sites for this study are shown in Figure 1. Out of 78 sites, 50% of the developments are located within the urban centers, and the remaining sites are in the nearby suburban areas of the City of Kelowna.

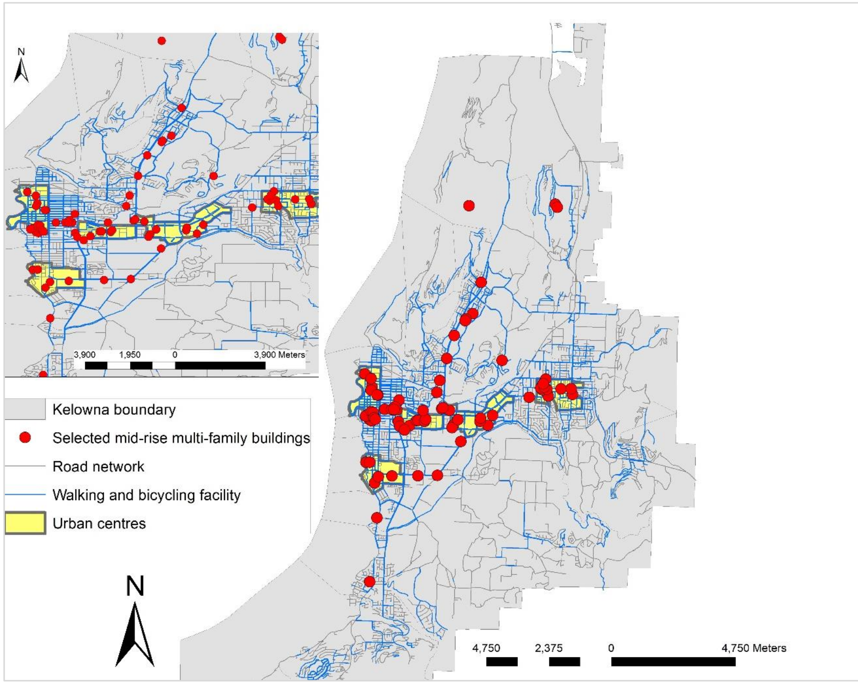

Figure 1. Study area

The survey includes two components: person count and intercept survey. In the case of the person count, a surveyor was stationed at each entry/exit door of the buildings to count the number of persons entering and exiting the building along with their travel mode. Person trips were the trips made by any travel mode by an individual person entering or exiting the residential development. Person trips were counted and categorized based on their travel modes. Surveyors documented the count of passenger vehicles and vehicle occupancy while crossing the cordon line. The cordon line was defined for each development during the reconnaissance such that surveyors could observe the vehicles entering/exiting the parking. To get the total person trip count for a development, passenger vehicle trip count was multiplied with vehicle occupancy and added with the walk/transit and bike trips. In the case of the intercept survey, surveyors approached people as they were entering or exiting the building to collect further information such as whether they were a visitor or resident, origin/destination of the trip, travel mode, home ownership type, and trip purpose among others. Based on these data, the residential component of count was identified. Data were recorded at a 15-minute interval during the evening peak hour (i.e., 4.00 to 6.00 pm) of weekdays from Tuesday to Thursday. Thus, the data collection procedure aligns with the recommended guidelines of ITE trip generation handbook 3rd edition (Hooper, 2017). For modeling purpose, this study categorized the trips as vehicular and non-vehicular trips. Vehicular trips were considered as the trips made by the passenger vehicles. On the other hand, non-vehicular trips were considered as the person trips made by transit/walk and bike.

5.2 Supplementary data source

Additional built environment data are collected from various resources. For example, neighborhood characteristics such as population density, percentage of single-detached houses, and employment density are collected from Census, Canada at the dissemination area (DA) level. Dwelling unit information of each site is retrieved from BC Assessment. Land-use data such as residential, commercial, park, and aquatic area are collected from Desktop Mapping Technologies Inc. (DMTI). Transportation infrastructure information including pedestrian and bicycle facility, bus routes, bus stops, and road network information are extracted from the Open Data, City of Kelowna, and BC Transit. Locations of activity points such as shopping centers, retail stores, and restaurants, among others are collected from DMTI. In the case of accessibility measures, distance from the sites to the central business district (CBD), distance to the nearest bus stops, and restaurants, among others are determined using the network analysis tool in ArcGIS. In addition, this study generates variables that have important policy implications. For example, variables that evaluate the influence of bike friendliness environment (Orvin & Fatmi, 2020b), street connectivity (Targa & Clifton, 2005), and land-use diversity (Mavoa et al., 2018) among others.

To capture the effects of the immediate surrounding area, the variables are generated at the spatial unit of 1 km road network-based buffer from each counting site using ArcGIS. For example, bike index (BI)[1] is generated for this 1-km buffer area, which is a measure of the overall bike friendliness of that area. BI is determined using several factors such as road and bike infrastructure, accessibility, topography, environment, and diversity characteristics among others (Hartanto et al., 2017; Orvin & Fatmi, 2020b). At first, considered factors are normalized using the maximum and minimum values based on their positive or negative impact on bike friendliness. In the next step, BI is measured by combining all the factors using an equal weightage. BI value ranges from 0 to 1, where a value closer to 1 signifies a higher bike friendly environment.

Land-use index (LUI)[2] is measured for each development to identify the diversity in land usage (Frank et al., 2005; Mavoa et al., 2018). Several land-use types including the residential, commercial, government and institutional, park and aquatic land use are considered in the calculation. LUI is expressed on a scale of 0 to 1, where a value closer to 1 indicates a heterogeneous land mix. Furthermore, road-connectivity index (RCI) is generated using a number of links and the number of road junctions (Agampatian, 2014). RCI is the ratio of the total number of links to total number of nodes.

6 Comparative analysis between the observed rates with ITE rates

Data reveals that around 72% of the trips are made using vehicles. The remaining 28% are non-vehicular trips including walk, bicycle, and transit trips. A comparative analysis of the observed trip rates with the ITE rates for mid-rise multi-family developments during the PM peak hour of weekdays is shown in Figure 2 – 4. The analysis suggests that the observed vehicle trip rates are consistently below the ITE rate (Figure 2a). The average observed vehicle trip rate is lower (mean = 0.32, standard deviation = 0.19) than that of ITE rate (mean = 0.41, standard deviation = 0.22). In the case of the person trip rates, similar observation of consistently low observed rates compared to the ITE rates can be made for the majority portion of the plot (Figure 2b). The average observed person trip rate is 0.49 with a standard deviation of 0.28 which is lower than the ITE average rate of 0.50 with a standard deviation of 0.08.

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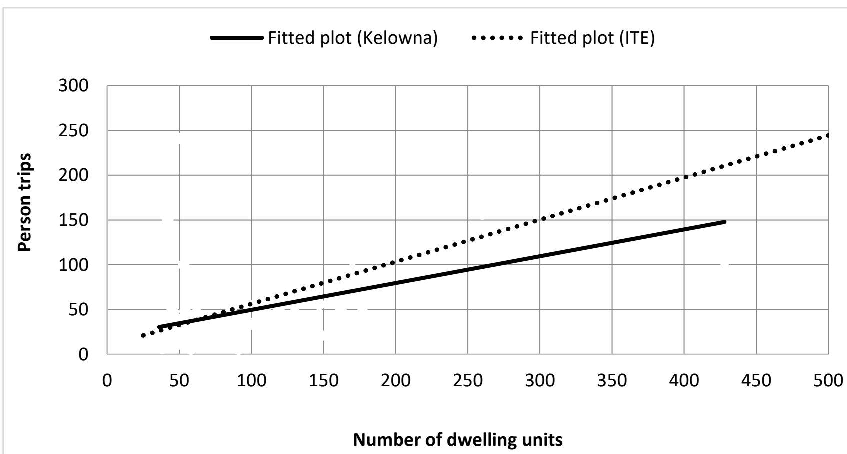
[1] BI= [(number of activity point*0.091) + (average distance to activity points*0.091) + (length of sidewalk*0.091) + (length of cycle infrastructure*0.091) + (ratio of cycle infrastructure to road length*0.091) + (percent rise in elevation*0.091) + (distance to nearest park*0.091) + (distance to nearest water body*0.091) + (distance to nearest transit*0.091) + (road-connectivity index*0.091) + (land-use index*0.091)]

[2] Land-use index = $(-1)*\sum_{s=1}^{S} L_i*\ln(L_i)/\ln(S)$

Here, L_i= proportion of land-use type (e.g., residential, commercial, park and aquatic land use among others),

S = number of land mix categories

(a) Vehicle trip rates



(b) Person trip rates

Figure 2. Vehicle and person trip rates for mid-rise multi-family (LUC 221) developments – Weekday, PM peak hour (4-6 pm)

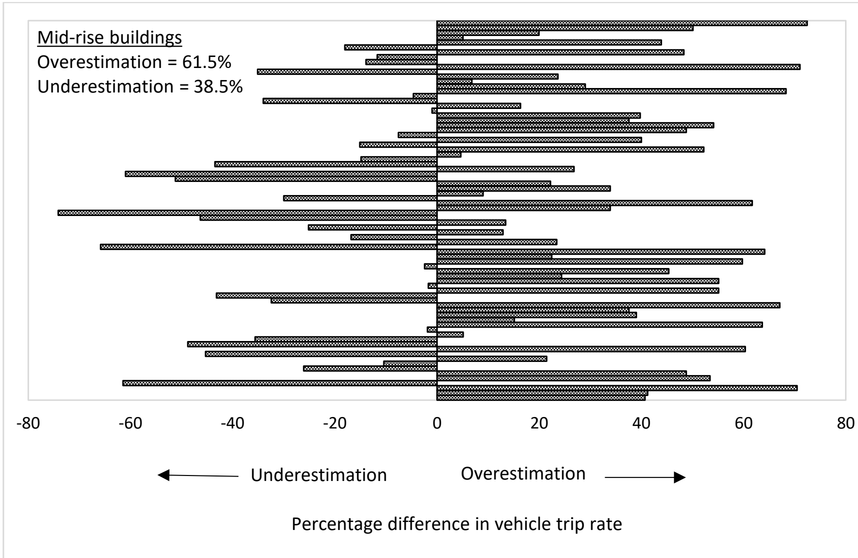


Figure 3. Difference between the ITE vehicle trip rates and observed vehicle trip rates in Kelowna for mid-rise, multi-family developments

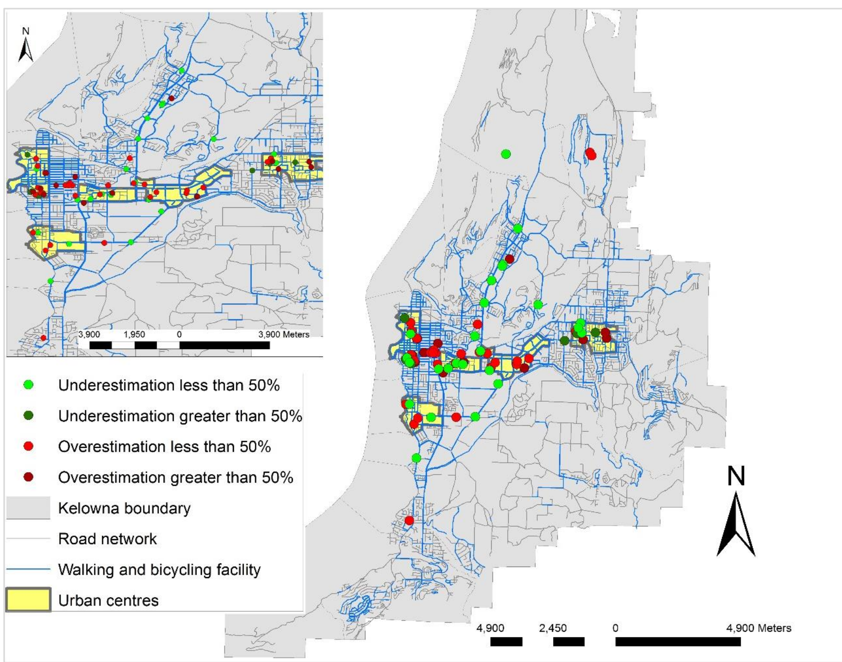
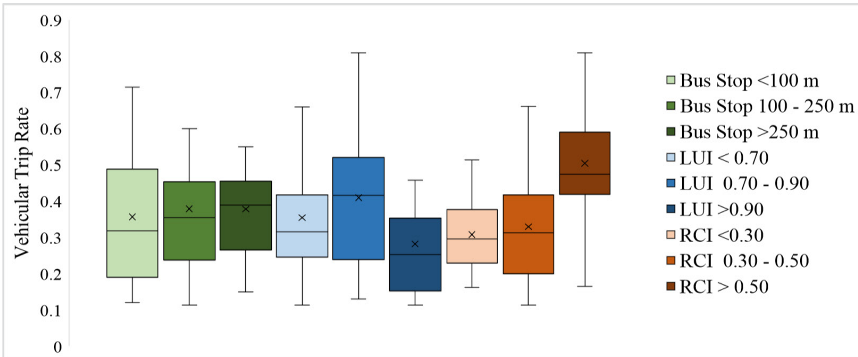
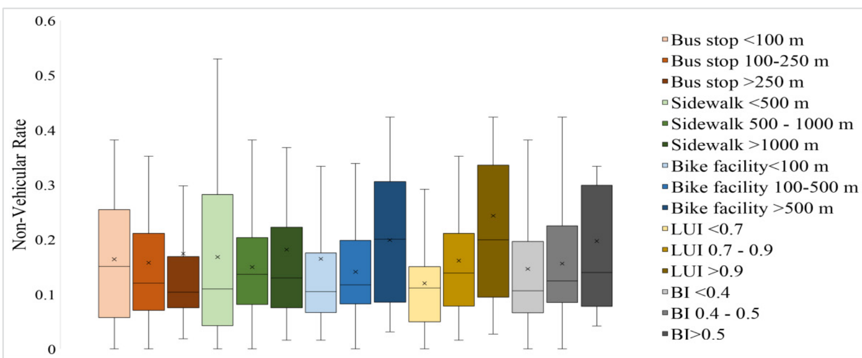


Figure 4. Spatial distribution of the overestimated and underestimated sites in Kelowna

Further analysis is performed by estimating the percentage difference between the ITE and observed vehicle trip rates. Note that overestimation refers that the ITE rate is greater than the observed rate, and underestimation indicates that the ITE rate is lower than the observed rate. The analysis results suggest that the ITE trip generation guideline overestimates in 61.5% of the cases and underestimates in 38.5% cases (Figure 3). Figure 3 reveals that overestimation is greater than 25% for about 41% of cases. On another note, underestimation less than 25% is observed for approximately 59% cases. The higher share of lower underestimation implies that ITE underestimated by a very small margin for a significant number of cases. Figure 4 shows the spatial distribution of overestimated and underestimated sites in Kelowna.



(a) Vehicular trip rates



(b) Non-vehicular trip rates

Figure 5. Distribution of vehicular and non-vehicular trip rates for mid-rise, multi-family developments with built environment attributes

Figure 5 illustrates the distribution of observed vehicular and non-vehicular trip rates (i.e., walk, bike, and transit trips) with built environment characteristics. Among the built environment characteristics, bus stop distance refers to the distance from study sites to the nearest bus stops. The rest of the built environment attributes are generated for the spatial unit of 1 km road network-based buffer from each study site. These attributes include land-use index (LUI), road-connectivity index (RCI), bike index (BI), length of the sidewalk, and length of the bicycle facility. In the case of the vehicular trip rates (Figure 5a), locations farther away from bus stops generate more vehicular trips. For example, the average vehicle trip rate for locations within 100 m of the bus stops is 0.35, which increased to 0.38 for locations farther than 250 m from the bus stops. In the case of LUI, average vehicle trip rate is lower (0.28) in higher mixed land-use areas than lower mixed land-use areas (0.35). For RCI, vehicle trip rate increases with RCI values.

In the case of non-vehicular trip rates (Figure 5b), locations farther away from bus stops generate less non-vehicular trips. For example, the average non-vehicular trip rate for locations within 100 m of the bus stops is 0.16, which is higher than the average rate of 0.10 for locations farther than 250 m from bus stops. For sidewalks and bicycle facilities, non-vehicular trip rates are found to incrementally increase with the increase in these active transportation infrastructures in the vicinity of the sites. Similarly, non-vehicular trip rates are higher in locations with higher mixed land use and bike index.

7 Model results

This study develops a latent segmentation-based negative binomial (LSNB) model to investigate the factors associated with the generation of vehicular and non-vehicular trips from mid-rise multi-family developments. This research develops two models: i) vehicular trip model, and ii) non-vehicular trip model. The models test the effects of the characteristics of the developments such as the number of dwelling units and built environment attributes such as land use, transportation infrastructure, neighborhood, and accessibility measures, among others. A summary statistic of the variables retained in the final models is presented in Table 1.

Table 1. Descriptive summary of variables

Variable name	Description	Vehicular trip		Non-vehicular trip	
		% or Mean	Std. dev.	% or Mean	Std. dev.
Dwelling units	Number of dwelling units in the building	89.17	67.68	89.17	67.68
Road-connectivity index	Road-connectivity index within 1 km buffer area of the development	0.46	0.18	0.46	0.18
Number of bus routes	Number of bus routes within 1 km buffer area of the development	-	-	3.63	2.08
Bike index	Bike index within 1 km buffer area of the development	-	-	0.44	0.08
Sidewalk length	Length of sidewalk in km within 1 km buffer area of the development	-	-	0.16	0.17
Land-use index	Land-use index within 1 km buffer area of the development	-	-	0.77	0.14
Land-use index greater than average	Dummy; If the land-use index within 1 km buffer area of the development is greater than the average of the sample = 1, else = 0	56.41	-	-	-
Percentage of residential area	Percentage of residential land use within 1 km buffer area of the development	42.40	20.33	-	-
Percentage area of the park and aquatic land use	Percentage area of the park and aquatic land use within 1 km buffer area of the development	-	-	10.63	9.79
Population density greater than average	Dummy; If population density in the dissemination area (DA) of the development is greater than average of the sample = 1, otherwise = 0	44.87	-	-	-
Percentage of single-detached house greater than average	Dummy; If the percentage of single-detached house in the dissemination area (DA) of the development is greater than the average of the sample = 1, else = 0	32.05	-	-	-
Employment density	The number of employed divided by the area of dissemination area (DA)	1795	1581	-	-
Distance to CBD greater than average	Dummy; If the distance from the development to the central business district is greater than the average of the sample =1, else = 0	39.74	-	-	-
Within urban centers	Dummy; If the development is within urban centers = 1, otherwise = 0	50.00	-	-	-
Outside urban center	Dummy; If the development is outside the urban centers = 1, otherwise = 0	-	-	50.00	-

7.1 Goodness-of-fit measures

The number of segments for the LSNB model is determined using AIC and BIC measures. In the case of the vehicular trip model, the LSNB model with two segments shows lower AIC and BIC measures of 610.4 and 659.8 respectively than that of the three segments model (AIC = 616.6, and BIC = 687.2). Therefore, the LSNB with two segments is considered as the final model for the vehicular trip generation. In the case of the non-vehicular trip generation, the LSNB model with two segments is considered as the final model based on the AIC and BIC measures. For comparison purposes, in addition to the LSNB model, this study develops latent segmentation-based Poisson regression (LSPR), latent segmentation-based linear regression (LSLR), Poisson regression (PR), negative binomial (NB), and linear regression (LR) models.

In the case of vehicular trips, the LSNB model outperforms the rest of the methods in-terms of adjusted pseudo rho-squared, AIC, and BIC measures. For instance, the adjusted pseudo rho-squared value for LSNB model is 0.963, for LSPR model is 0.961, for LSLR model is 0.962, for NB model is 0.312, for PR model is 0.567, and for LR model is 0.769 (Table 2). Only, the NB model shows a lower BIC measure (646.2) than LSNB model (659.8). However, the LSNB model reveals lower AIC measures, as well as capturing heterogeneity. In addition, LSNB model fits the dispersed data well. Therefore, for the vehicular trips, the LSNB model is considered to fit the data best. Similarly, for non-vehicular trips, the LSNB model fits the data best. Therefore, both for the vehicular and non-vehicular trip generation, the LSNB model with two segments is considered for further discussion. The estimation results of the LSNB models for vehicular and non-vehicular trips are reported in Table 3 and 4 respectively. The results suggest that the majority of the variables are statistically significant to at least at the 10% level in one latent segment.

Table 2. Goodness-of-fit measures of the models

	Vehicular Trip Model				Non-vehicular Trip Model			
	LL function	Adjusted pseudo rho-squared	AIC	BIC	LL function	Adjusted pseudo rho-squared	AIC	BIC
LSNB								
	-284.19	0.963	610.4	659.8	-259.87	0.907	553.7	593.8
LSPR	-306.55	0.961	651.1	695.8	-271.29	0.903	572.6	607.9
LSLR	-299.19	0.962	640.4	689.8	-290.14	0.896	614.3	654.3
NB	-303.52	0.312	625.0	646.2	-270.02	0.415	554.0	570.5
PR	-441.25	0.567	898.5	917.3	-461.88	0.235	935.8	949.9
LR	-559.47	0.769	1132.9	1149.4	-431.62	0.282	873.2	885.0

Table 3. Results of the LSNB model for vehicular trips

Attributes	Segment 1		Segment 2	
	coefficient	p-value	coefficient	p-value
Latent Segment Allocation Results				
Constant	0.14	0.7994	reference	
Population density greater than average	-2.72**	0.0389	reference	
Percentage of single-detached house greater than average	2.87***	0.0069	reference	
Parameter Estimation Results				
Constant	2.796***	0.0000	1.429***	0.0047
Dispersion parameter	31.790	0.2614	15.303	0.1160
Dwelling units	0.008***	0.0000	0.014***	0.0000
Road-connectivity index	0.495	0.3796	1.347**	0.0271
Land-use index greater than average	0.233	0.2264	-0.418	0.1645
Percentage of residential area	0.006	0.1111	-0.001	0.8295
Employment density	-0.061***	0.0000	0.006	0.1233
Distance to CBD greater than average	-0.530***	0.0021	0.880***	0.0002
Within urban centers	-0.190	0.2352	-0.151	0.2647

*** significance at 1% level, ** significance at 5% level, * significance at 10% level

7.2 Vehicular trip model

7.2.1 Model results of the latent segment allocation component

Table 3 presents the latent segment allocation component and parameter estimation results for the vehicular trip model. The segment allocation component retains the following variables: population density greater than average, and the percentage of single-detached house greater than average. The model is estimated assuming segment 2 as the reference segment. The model results suggest that population density greater than average shows a negative relationship in segment 1. This indicates that developments in relatively higher population density areas are less likely to be included in segment 1. On the other hand, developments in relatively densely populated areas are more likely to be included in segment 2. Furthermore, the positive relationship of the variable representing the percentage of single-detached houses greater than average reveals that developments in a higher share of single-detached houses have a higher likelihood to be assigned to segment 1. Therefore, segment 1 can be identified to include developments in suburban areas with lower population density and a higher percentage of single-detached houses. In the contrary, segment 2 can be identified to include developments in urban areas with a higher population density and a lower percentage of single-detached houses.

7.2.2 Parameter estimation results

This model confirms the effects of the number of dwelling units in the building and built environment attributes such as road-connectivity index, land-use index, the share of residential land use, developments within urban centers, employment density, and distance to the CBD for the generation of vehicular trips (Table 3). For example, the number of dwelling units show a positive relationship. This implies that developments with a higher number of dwelling units will generate a higher number of vehicle trips in urban and suburban areas. Road-connectivity index positively influences vehicle trips, since higher connectivity might offer better and convenient vehicle routing options. The variable representing land-use mix index greater than average shows heterogeneity across the segments. This variable shows a positive relationship for segment 1, which include suburban areas. This finding suggests that increasing land-use index in the suburban areas does not necessarily decrease vehicle trip generation. Lack of walking, bicycling, and transit infrastructures in such suburban areas might generate higher vehicle trips, despite heterogeneous land uses. On the other hand, the negative relationship for segment 2 suggests that increased land-use mix decreases vehicle trip generation in urban areas.

Similar heterogeneity is found for the variable representing the percentage of the residential area. The positive relationship for segment 1 refers that vehicle trips increase with an increase in the share of residential land use in suburban areas. In contrast, the same variable shows a negative relationship for segment 2, which indicates that vehicle trips decrease in the urban areas. For developments within the urban centers, a negative relationship is confirmed. This might be attributed to the high-density mix land use, and well-connected active transportation and transit infrastructures of the Kelowna urban centers. Employment density reveals a negative relationship for segment 1, implying that higher job opportunities in suburban areas reduce vehicle trip generation. In contrast, a positive relationship is found for segment 2. In the case of developments farther away from CBD, vehicle trip generation increases in segment 2.

7.3 Non-vehicular trip model

7.3.1 Model results of the latent segment allocation component

In the case of the non-vehicular trip model, the negative sign of land-use index suggests that developments in lower mixed land-use areas are included in segment 1 (Table 4). A positive relationship is found for the variable representing developments outside urban centers interacted with road-connectivity index. Overall, segment 1 can be identified to include developments in suburban areas which are outside urban centers with a higher road-connectivity and homogenous land use. On the other hand, segment 2 includes developments in urban areas.

7.3.2 Parameter estimation results

The model results suggest that the number of dwelling units in the building and built environment attributes such as the number of bus routes, bike index, length of the sidewalk, and percentage of aquatic and park areas are the determinants for the generation of non-vehicular trips (Table 4).

Table 4. Results of the LSNB model for non-vehicular trips

Attributes	Segment 1		Segment 2	
	coefficient	p-value	coefficient	p-value
Latent Segment Allocation Results				
Constant	9.00*	0.0516	reference	
Land-use index	-11.56**	0.0437	reference	
Outside urban center*road-connectivity index	3.92	0.1712	reference	
Parameter Estimation Results				
Constant	-0.585	0.5665	3.008***	0.0047
Dispersion parameter	9.968	0.4537	3.108***	0.0088
Dwelling units	0.016***	0.0000	0.003*	0.0994
Number of bus routes	-0.275***	0.0058	0.082	0.2537
Bike index	7.253**	0.0178	-3.942	0.2125
Sidewalk length	-5.970***	0.0002	1.358	0.1070
Percentage area of park and aquatic land use	0.077*	0.0841	0.029*	0.0719

*** significance at 1% level, ** significance at 5% level, * significance at 10% level

Similar to vehicular trips, the number of dwelling units positively influence the generation of non-vehicular trips. Higher percentage of parks and aquatic land-use areas are found to increase non-vehicular trips. Interestingly, the number of bus routes, bike index, and sidewalk length show heterogeneity across the segments. For instance, the number of bus routes and sidewalk length show positive signs in segment 2, which includes developments in urban areas. This implies that increasing transit accessibility and walk supportive infrastructures such as higher number of bus routes and sidewalk lengths in the urban areas increase non-vehicular trips. In contrast, a negative relationship in segment 1 suggests that increase of the number of bus routes and length of sidewalks in suburban areas do not necessarily increase non-vehicular trips. This might be attributed by the longer distance among destinations in suburban areas, further illustrating the need for dense developments coupled with transit and active transportation infrastructure to promote non-vehicular trips. Interestingly, the bike index shows a positive relationship in segment 1. This implies that non-vehicle trips are more likely to increase with the increase of bike index in suburban areas.

7.4 Elasticity results

To determine the relative importance of variables and their magnitude of impact, it is important to estimate the elasticity effects of the explanatory variables. Aggregate-level elasticities are estimated for the explanatory variables of both vehicular and non-vehicular trip models based on the overall sample (Nashad et al., 2016). Elasticity results indicate the percentage change in the likelihood of expected number of trips caused by a unit percentage change of a specific explanatory variable, considering the other variables unchanged. In the case of the vehicular trip model, results reveal that the variables representing the dwelling units and road-connectivity index have substantial positive magnitude of impact on the likelihood of number of vehicular trips (Table 5). For example, probability of vehicle trip generation might increase by 1.04% with unit percentage increase in dwelling units. Road-connectivity index shows a 0.44% increase in the probability of generating vehicular trips. On the other hand, results suggest a significant negative magnitude of impact for variable representing the employment density. For instance, unit percentage increase in employment density contributes to a decrease of the likelihood of vehicular trips by 0.45%. It is also observed that variable representing the developments within urban centers is more elastic than that of land-use index.

In the case of the non-vehicular trip model, variables representing the dwelling units and sidewalk length show a substantial impact (Table 5). For example, percentage increase in dwelling units increases the probability of non-vehicular trips by 0.67%. The magnitude of impact for the variable representing the sidewalk length is 1.9 times than bike index. Furthermore, percentage area of park and aquatic land use increases the probability of non-vehicular trips by 0.16%. Results imply that in addition to dwelling units, an increased bicycle-friendly environment and sidewalk facility might influence non-vehicular trips significantly.

Table 5. Elasticity results

Attributes	**Elasticity**
Vehicular trip model	
Dwelling units	1.04***
Road-connectivity index	0.44**
Land-use index greater than average	-0.06
Percentage of residential area	0.10
Employment density	-0.45***
Distance to CBD greater than average	0.09
Within urban centers	-0.08*
Non-vehicular trip model	
Dwelling units	0.67***
Number of bus routes	-0.23
Bike index	0.09
Sidewalk length	0.17**
Percentage area of park and aquatic land use	0.16

*** significance at 1% level, ** significance at 5% level, * significance at 10% level

7.5 Predictive performance evaluation of the models

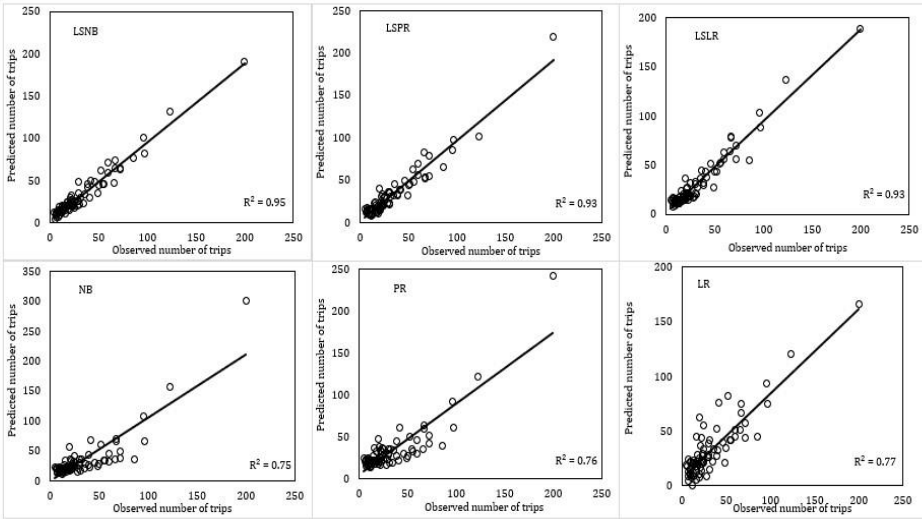
The predictive performance of the LSNB model is assessed by comparing: i) the predictive performance measures (Table 6), and ii) plot of predicted trips against the observed trips (Figure 6) for different models. Several goodness-of-fit measures are used to assess the performance, which includes the Mean Prediction Bias (MPB), Mean Absolute Deviation (MAD), and Mean Squared Prediction Error (MSPE) (Yasmin & Eluru, 2016). These measures quantify the errors associated with the predictions. The model with a lower MPB, MAD, and MSPE value provides better prediction accuracy. In the case of vehicular trip model, results suggest that MPB, MAD, and MSPE measures of the LSNB model reveal a higher prediction accuracy than the LSPR, LSLR, NB, PR, and LR models. For instance, the LSNB reveals a MAD value of 5.38, which is smaller than that of LSPR (6.45), LSLR (5.81), NB (12.73), PR (11.14), and LR (10.67) models. Figure 6 also illustrates that the LSNB model provides reasonably satisfactory prediction accuracy compared to the other models. For example, plot of predicted vs observed trips reveals that the r-squared value for LSNB model is higher (i.e., 0.95) compared to the LSPR (0.93), LSLR (0.93), NB (0.75), PR (0.76), and LR (0.77) models. In the case of non-vehicular trips, r-squared values for the models are found as: LSNB (0.89), LSPR (0.90), LSLR (0.64), NB (0.19), PR (0.29), and LR (0.27). However, LSNB model shows a MAD value of 3.59 which is smaller than the MAD value for the rest of the models (Table 6). Therefore, it can be concluded that the LSNB model provides reasonably satisfactory accuracy for estimating the vehicular and non-vehicular trips.

Table 6. Predictive performance evaluation of the models

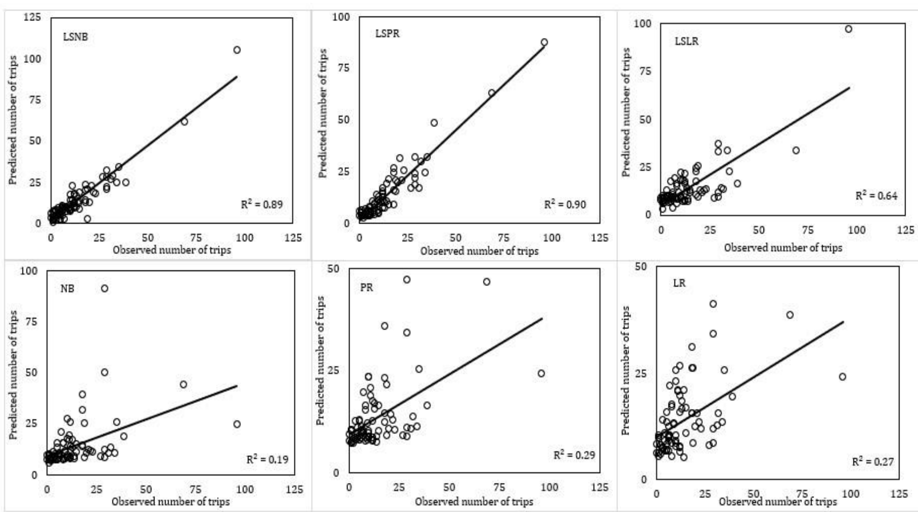
Model	**Goodness-of-fit measures**					
	Vehicular Trip Model			**Non-vehicular Trip Model**		
	MPB	MAD	MSPE	MPB	MAD	MSPE
LSNB	-0.21	5.38	45.48	0.23	3.59	19.11
LSPR	-0.31	6.45	65.41	-0.26	3.60	21.94
LSLR	-0.86	5.81	59.44	0.24	6.68	77.53
NB	2.38	12.73	701.75	0.62	9.09	207.42
PR	0.23	11.14	222.25	-0.24	8.30	153.06
LR	-0.25	10.67	208.59	0.23	8.54	156.53

$$MPB = \frac{\sum_{n=1}^{N} (Y_p - Y_o)}{N}, \quad MAD = \frac{\sum_{n=1}^{N} |Y_p - Y_o|}{N}, \quad MSPE = \frac{\sum_{n=1}^{N} (Y_p - Y_o)^2}{N}$$

Here, Y_p = Predicted value, Y_o = observed value, and N = total observation



(a) Vehicular trip



(b) Non-vehicular trip

Figure 6. Predicted vs. observed trips

7.6 Model implications

This study develops a latent segmentation-based negative binomial (LSNB) model for estimating vehicular and non-vehicular trip generation from mid-rise multi-family residential developments. Developed models analyze the micro-level influence of size of the development and surrounding built environment attributes. Furthermore, developed models capture unobserved heterogeneity by assigning development sites into discrete latent segments. Discounting such unobserved heterogeneity might result in biased estimation and inconsistent forecasting. The interpretation of model results provides important and interesting insight to the practitioners. For example, increasing land-use index in the suburban areas does not necessarily decrease vehicular trip generation. Non-existence of walking, bicycling, and transit infrastructures in such suburban areas might contribute to higher vehicle trips, despite diverse land mix. Residential developments within the urban centers might influence vehicular trips negatively due the heterogeneous land use, and well-connected active transportation and transit infrastructures within the urban centers. Number of bus routes, bike index, length of the sidewalk, and percentage of aquatic and park areas significantly influence non-vehicular trips. Increasing transit accessibility and walk-friendly infrastructures in the urban areas might encourage non-vehicular trips. City planners will find the parameter estimation results beneficial to precisely predict the multi-modal trips. Elasticity results will assist the decision-makers to plan effectively by identifying the critical factors contributing to vehicular and non-vehicular trips.

8 Conclusions

This paper investigates the vehicular and non-vehicular trip generation of mid-rise multi-family residential developments. This study collects trip generation information from 78 mid-rise multi-family residential buildings in Kelowna, Canada. The observed vehicle trip rates and person trip rates for the weekdays pm peak period are compared with the ITE rates. The comparative analysis suggests that the observed rates are consistently below the ITE rates. This motivated the development of an advanced method to improve the prediction accuracy of trip generation models. Specifically, a latent segmentation-based negative binomial (LSNB) model is developed utilizing the trip generation information of Kelowna. One of the key features of this study is to capture unobserved heterogeneity by formulating a flexible segment allocation model within the LSNB framework. This segment allocation component distributes mid-rise buildings across the urban context into discrete latent segments. Another unique feature of this study is to test the combined influence of the size of the proposed building such as the number of dwelling units, and the surrounding built environment attributes such as land use, transportation infrastructure, neighborhood, and accessibility characteristics. To determine the relative importance of variables and their magnitude of impact, aggregate-level elasticity effects are estimated for the explanatory variables.

This study develops two LSNB models for estimating vehicular and non-vehicular trips. The performance of the LSNB models for both cases is evaluated by comparing their goodness-of-fit measures with five other methods such as LSPR, LSLR, NB, PR, and LR models. During the estimation process, the models are evaluated using their log-likelihood function, adjusted pseudo rho-squared, AIC, and BIC measures. The results suggest that the LSNB model out-performs other models by fitting the data best. In addition, the predictive performance of the models is assessed using MPB, MAD, and MSPE measures. Again, the LSNB model outperforms the rest of the methods with minimal error in prediction. Therefore, the LSNB model is considered for further discussion of the results.

In the case of the LSNB model for vehicular trips, the segment allocation model results suggest that segment 1 can be identified to include developments in suburban areas with a lower population density and a higher percentage of single-detached houses. In contrast, segment 2 includes developments in urban areas. The model results suggest that the number of dwelling units and road-connectivity index are associated with increased vehicular trips. Developments within urban centers are likely to reduce vehicular trips. Determinants such as land-use index, percentage of the residential area, employment density, and distance to CBD show significant heterogeneity across the segments. For example, increasing land-use mix in the urban areas has a higher probability to decrease the generation of vehicular trips. On the other hand, vehicular trip generation is likely to be higher in suburban areas, despite increasing land-use mix index. Another interesting finding is that higher residential developments in urban areas are associated with decreased vehicular trips. Elasticity results reveal a substantial magnitude of impact for dwelling units, road-connectivity index, employment density, and distance to CBD, among others.

In the case of the non-vehicular trips, segment allocation model results suggest that segment 1 is likely to include developments in suburban areas; whereas, segment 2 includes developments in urban areas. The model results reveal that the number of dwelling units and the percentage of the park and aquatic areas are associated with increased generation of non-vehicular trips. The model also confirms significant heterogeneity across the segments. For example, higher number of bus routes and longer length of sidewalks reveal a higher likelihood to increase non-vehicular trips in urban areas. In contrast, non-vehicular trip generation is lower in suburban areas, despite increasing the number of bus routes and sidewalk lengths. One of the interesting findings is that increased bike index in the suburban areas is likely to increase non-vehicular trips. Elasticity results suggest that dwelling units, bicycle-friendly environment, park and lake land development, and sidewalk facility might contribute to a higher number of non-vehicular trips.

This study has certain limitations. For example, parking data such as parking availability and pricing was not available which is critical to predict the vehicular traffic. Previous studies reported that restricted parking affects vehicular trips, specially within the compact neighborhoods with sufficient facilities for walking, biking, and transit modes (Christiansen et al., 2017; Hamre & Buehler, 2014). One of the future research scopes could be collecting parking availability information for the developments to evaluate the vehicular trips more accurately. This study estimated the vehicular and non-vehicular trips independently to improve the existing vehicular and person-based approach of ITE. However, choice of vehicular and non-vehicular trips might be interactive and substitutive. Trip purpose might also affect the mode choice. Further research should be done to identify the inter-dependency between the vehicular and non-vehicular trips. Future research should focus on jointly modeling the vehicular and non-vehicular trips. Another limitation is that few variables are included in the developed model even though not statistically significant. These variables are retained in the final model since they have important policy implications. Future research should focus on building the model using a larger data set and compare the statistical significance of these parameters. Furthermore, surveyors did not record data regarding the presence of bottom-floor retail and internal connections between uses. This is identified as another limitation of this study. Moreover, participation in the intercept survey was voluntary and, in many cases, people declined to participate and share information. Therefore, this study could not distinguish the walk and transit trips precisely and aggregated the non-vehicular trips which include walk, bike and transit trips. Future research should focus on developing mode-specific trip generation models. To prevent overestimation or underestimation of count and improve the precision of count by different modes, video cameras should be utilized. In summary, the findings of this study provide important insights towards the need for improving the ITE trip generation guidelines; particularly, efforts are required to develop multi-modal trip generation guidelines. This study further confirms the need to incorporate the combined effects of the built environment characteristics and the size of the proposed developments. This research proposes a methodology to improve the vehicular and non-vehicular trip generation estimates. The heterogeneity captured in this study needs to be accommodated within the policies to accurately estimate the generation of multi-modal trips. The elasticity analysis reveals important policy-making insights based on the most influential factors. Finally, the findings are expected to assist transportation planners and engineers in developing policies and transportation infrastructure investment decision-making.

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Data availability

Data is restricted as per Research Ethics Board approval due to the identifying information of the individuals attached with the dataset. However, the aggregate representation of data analysis is presented in the paper.

References

Acuere Consulting Inc. (2015). Survey design and conduct. 2013 Okanagan Travel Survey. Retrieved from https://www.smarttrips.ca/sites/files/6/docs/2013_okanagan_travel_survey_-_1._design_conduct_v1.4.pdf

Agampatian, R. (2014). *Using GIS to measure walkability: A case study in New York City* (Disseration), School of Architecture and the Built Environment, Stockholm. Retrieved from http://urn.kb.se/resolve?urn=urn:nbn:se:kth:diva-145011

Anastasopoulos, P., & Mannering, F. (2009). A note on modeling vehicle accident frequencies with random-parameters count models. *Accident Analysis & Prevention, 41*(1), 153–159.

Arrington, G., & Cervero, R. (2008). *Effects of TOD on housing, parking, and travel* (Technical report, TCRP report 128, project H-27A.) Retrieved from http://www.montgomeryplanning.org/transportation/documents/TCRPReport128TOD.pdf

Ashqar, H., Elhenawy, M., Rakha, H., Road, V., & Qld, K. (2019). Modeling bike counts in a bike-sharing system considering the effect of weather conditions. *Case Studies on Transport Policy, 7*(2), 261–268. https://doi.org/10.1016/j.cstp.2019.02.011

Association of Bay Area Governments. (2008). *Trip-generation rates for urban infill land uses in California.* Oakland, CA: Association of Bay Area Governments.

Cai, Q., Lee, J., Eluru, N., & Abdel-aty, M. (2016). Macro-level pedestrian and bicycle crash analysis: Incorporating spatial spillover effects in dual state count models. *Accident Analysis and Prevention, 93*, 14–22. https://doi.org/10.1016/j.aap.2016.04.018

Chen, F., Ma, X., Chen, S., & Yang, L. (2016). Crash frequency analysis using hurdle models with random effects considering short-term panel data. *International Journal of Environmental Research and Public Health, 13*(1043), 1–11. https://doi.org/10.3390/ijerph13111043

Christiansen, P., Engebretsen, Ø., Fearnley, N., & Usterud Hanssen, J. (2017). Parking facilities and the built environment: Impacts on travel behavior. *Transportation Research Part A: Policy and Practice, 95,* 198–206. https://doi.org/10.1016/j.tra.2016.10.025

City of Kelowna. (2018a). *Facts in focus: Transportation.* Kelowana, BC: City of Kelowana. Retrieved from https://www.kelowna.ca/sites/files/1/docs/related/ff-transportation.pdf

City of Kelowna. (2018b). *Facts in focus: Population & housing in Kelowna.* Kelowana, BC: City of Kelowana. Retrieved from https://www.kelowna.ca/sites/files/1/docs/related/ff-population_and_housing.pdf

City of Kelowna. (2019). *Roads & transportation.* Kelowana, BC: City of Kelowana. Retrieved from https://www.kelowna.ca/roads-transportation/active-transportation/benefits-active-transportation

Clifton, K., & Currans, K. (2019-July). *Characterizing the trip generation profiles of multifamily housing* (NITC-RR-878). Portland: Portland State University. Retrieved from https://doi.org/10.15760/trec.231

Clifton, K., Currans, K., & Muhs, C. (2015). Adjusting ITE's trip generation handbook for urban context. *Journal of Transport and Land Use, 8*(1), 5. https://doi.org/10.5198/jtlu.2015.378

Comer, J., Rose, N., & Bombom, L. (2014). Poisson regression analysis of highway fatality accident data in Oklahoma. *International Journal of Applied Geospatial Research, 5*(4), 72–86.

Currans, K., Abou-zeid, G., Clifton, K., & Howell, A. (2020). Improving transportation impact analyses for subsidized affordable housing developments: A data collection and analysis of motorized vehicle and person trip generation. *Cities, 103*(May 2019), 102774. https://doi.org/10.1016/j.cities.2020.102774

Ewing, R., Tian, G., Goates, J., Zhang, M., Greenwald, M., Joyce, A., … & Greene, W. (2015). Varying influences of the built environment on household travel in 15 diverse regions of the United States.

Urban Studies, 52(13), 2330–2348. https://doi.org/10.1177/0042098014560991

Evans, J., Bhatt, K., & Turnbull, K. (2003). *Road value pricing: Traveler response to transportation system changes* (TCRP report 95). Washington DC: Transportation Research Board, Transit Cooperative Research Progam. Retrieved from http://onlinepubs.trb.org/onlinepubs/tcrp/tcrp_rpt_95c14.pdf

Frank, L., Schmid, T., Sallis, J., Chapman, J., & Saelens, B. (2005). Linking objectively measured physical activity with objectively measured urban form: Findings from SMARTRAQ. *American Journal of Preventive Medicine, 28*(2), 117–125.

Gard, J. (2007). Innovative intermodal solutions for Urban Transportation Paper Award: Quantifying transit-oriented development's ability to change travel behavior. *ITE Journal, 77*(11), 42–46.

Garver, M., Williams, Z., & Taylor, G. (2008). Employing latent class regression analysis to examine logistics theory: An application of truck driver retention. *Journal of Business Logistics, 29*(2), 233–257.

Greene, W., & Hensher, D. (2003). A latent class model for discrete choice analysis: Contrasts with mixed logit. *Transportation Research Part B: Methodological, 37*(8), 681–698. https://doi.org/10.1016/S0191-2615(02)00046-2

Gulden, J., Goates, J., & Ewing, R. (2013). Mixed-use development trip generation model. *Transportation Research Record, 2344*(1), 98–106. https://doi.org/10.3141/2344-11

Hamre, A., & Buehler, R. (2014). Commuter mode choice and free car parking, public transportation benefits, showers/lockers, and bike parking at work: Evidence from the Washington, DC region. *Journal of Public Transportation, 17*(2), 67–91. https://doi.org/10.5038/2375-0901.17.2.4

Handy, S., Shafizadeh, K., & Schneider, R. (2013-March). *California smart-growth trip generation rates study.* Sacramento: California Department of Transportation.

Hartanto, K., Grigolon, A., van Maarseveen, M., & Brussel, M. (2017). *Developing a bikeability index in the context of transit-oriented development (TOD).* Paper presented at the 15th International Conference on Computers in Urban Planning and Urban Management (CUPUM), Cambridge, MA, July 7–10.

Hooper, K. (2017). Trip generation handbook (3rd ed.). Washington, DC: Insitute Transportation Engineers.

Institute of Transportation Engineers. (2004). *Trip generation handbook: An ITE recommended practice* (2nd ed.). Washington, DC: Insitute of Transportation Engineers.

Institute of Transportation Engineers. (2017). *Trip generation manual* (Vol. 2, Issue September). Washington, DC: Insitute of Transportation Engineers.

Institute of Transportation Engineers. (2020). *Trip generation manual* (10th edition) supplement. Washington, DC: Insitute of Transportation Engineers.

Khan, N., Fatmi, M., & Habib, M. (2017). Type choice behavior of alternative fuel vehicles: A latent class model approach. *Transportation Research Procedia, 25,* 3299–3313.

Lapham, M. (2001). *Transit oriented development: Trip generation and mode split in the Portland metropolitan region.* Portland: Portland State University, Center for Urban Studies. Retrieved from http://pdxscholar.library.pdx.edu/cus_pubs/52

Mansoureh, J., & Ricardo, C. (2010). *Trip generation studies for special generators* (Research report, project number MD-09-SP808B4J). Baltimore: Maryland State Highway Administration. https://rosap.ntl.bts.gov/view/dot/17704

Mavoa, S., Boulangé, C., Eagleson, S., Stewart, J., Badland, H., Giles-Corti, B., & Gunn, L. (2018). Identifying appropriate land-use mix measures for use in a national walkability index. *Journal of Transport and Land Use, 11*(1), 681–700.

Motoaki, Y., & Daziano, R. (2015). A hybrid-choice latent-class model for the analysis of the effects of weather on cycling demand. *Transportation Research Part A: Policy and Practice, 75,* 217–230.

Nashad, T., Yasmin, S., Eluru, N., Lee, J., & Abdel-Aty, M. (2016). Joint modeling of pedestrian and bicycle crashes: Copula-based approach. *Transportation Research Record, 2601,* 119–127. https://doi.org/10.3141/2601-14

Orvin, M., & Fatmi, M. (2020a). Modeling destination choice behavior of the dockless bike sharing service users. *Transportation Research Record, 2674*(11), 875–887. https://doi.org/10.1177/0361198120950315

Orvin, M., & Fatmi, M. (2020b). Why individuals choose dockless bike sharing services? *Travel Behavior and Society, 22,* 199–206. https://doi.org/10.1016/j.tbs.2020.10.001

Poch, M., & Mannering, F. (1996). Negative binomial analysis of intersection-accident frequencies. *Journal of Transportation Engineering, 122*(2), 105–113.

Revelt, D., & Train, K. (1998). Mixed logit with repeated choices: Households' choices of appliance efficiency level. *Review of Economics and Statistics, 80*(4), 647–657.

Schneider, R., Shafizadeh, K., Sperry, B., & Handy, S. (2013). Methodology to gather multimodal trip generation data in smart-growth areas. *Transportation Research Record: Journal of the Transportation Research Board, 2354*(1), 68–85. https://doi.org/10.3141/2354-08

Shafizadeh, K., Lee, R., Niemeier, D., Parker, T., & Handy, S. (2012). Evaluation of operation and accuracy of available smart growth trip generation methodologies for use in California. *Transportation Research Record, 2307*(1), 120–131.

Tabeshian, M., & Kattan, L. (2014). Modeling nonmotorized travel demand at intersections in Calgary, Canada: Use of traffic counts and geographic information system data. *Transportation Research Record, 2430*(1), 38–46.

Targa, F., & Clifton, K. (2005). The built environment and trip generation for non-motorized travel. *Journal of Transportation and Statistics, 8*(3), 55–70.

Tian, G., Ewing, R., White, A., Hamidi, S., & Walters, J. (2015). Traffic generated by mixed-use developments thirteen-region study using consistent measures of built environment. *Transportation Research Record, 2500,* 116–124. https://doi.org/10.3141/2500-14

Traffic Analysis & Design Inc. (2017). *Mixed-use development (MXD) trip generation study* (Technical report). Appleton, WI: Wisconsin Department of Transportation. Retrieved from https://wisconsindot.gov/dtsdManuals/traffic-ops/manuals-and-standards/mxd-study.pdf

Virginia Department of Transportation. (2013-April). *Traffic impact analysis regulations administrative guidelines* (Technical report, 24VAC30-155). Richmond, VA: Virginia Department of Transportation. Retrieved from https://www.virginiadot.org/projects/resources/TIA_Administrative_Guidelines.pdf

Yasmin, S., & Eluru, N. (2016). Latent segmentation based count models: Analysis of bicycle safety in Montreal and Toronto. *Accident Analysis & Prevention, 95,* 157–171.