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Impact of road features on shared e-scooter trip volume: A study based on multiple membership multilevel model

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ABSTRACT

E-scooter sharing systems have been widely adopted by cities around the world. Previous studies analyzed community-level factors influencing e-scooter usage. Few studies examined the effect of road features on e-scooter trip volume (ETV) of the road segment, which can reveal the road features that riders prefer. This study explores this topic by analyzing the ETV of 29,544 road segments in Calgary, Canada, while controlling for community-level factors. Because some segments are the boundaries of multiple communities, the multiple membership multilevel model is adopted to tackle this boundary problem. The results show that segments with sidewalks, dedicated bicycle facilities, lower speed limit, more street lights and trees have higher ETV. ETV is also higher in communities with high income, high percentage of commercial and residential area. Quantifying the effect of road features on ETV could help government agencies determine where e-scooters should be ridden and design road facility improvement plans for e-scooter users.

1. Introduction

As a new type of shared micro-mobility, e-scooter sharing (ESS) could provide door-to-door service with a fewer physical effort from users than bike sharing due to its features of electric drive. Despite its short history, ESS has been widely adopted by many cities around the world. In the United States alone, up to November 2019, ESS has been implemented in more than 100 cities (Urban, 2020). Many city administrators have realized the important role that ESS plays in the urban transportation system and have begun to discuss the regulation policies toward e-scooter as well as improvement of road infrastructure for e-scooter riding. Most of the discussion centered on what type of road infrastructure that e-scooter should be ridden. So far, different cities have very different policies and rules. For example, e-scooter is forbidden to be used on sidewalks in Brisbane but can be used on bicycle lanes and other facilities. In Christchurch, New Zealand, e-scooter is classified as "low-powered vehicles" and can be ridden on sidewalks or bikeways, but not on the roadways. In Calgary, Canada, the government has designated e-scooter should be mainly ridden on bike paths and sidewalks.

To make the appropriate policies, government agencies should understand what type of road do e-scooter riders prefer to ride on. As a result, this study makes an effort to explore the relationship between road features and ETV to shed light on the preferences of scooter users. While route choice behavior analysis is the classical way to study this topic, due to the unavailability of such type of data, we propose an alternative method. By assuming that the preferred road segments would be used by e-scooter riders more frequently, we can study the relationship between the e-scooter trip volume (ETV) and features of a road segment while controlling for built environment factors of surrounding communities that influence the e-scooter demand to understand what type of road features are favored by e-scooter riders.

The ESS pilot program in Calgary, Canada, was carried out in 2019. The program recorded the shared ETV on each road segment (29,544 road segments in total). The data has been made available to the public. We used this dataset used for modeling and analysis. Since the pilot

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program only provides trip data for three months (July, August, and September), the data for the months are used. Two types of variables are considered: segment features and built environment factors of surrounding communities that influence the ETV. However, when including the built environment factors in the model, the unobserved heterogeneity problem may arise due to the fact that several segments could fall within one community, which possibly leads to a correlation between these segments. Thus, as a widely accepted method to deal with this unobserved heterogeneity problem, the multilevel modeling approach is adopted in this study.

On the other hand, because some road segments are the boundaries of many communities, the user's choice of riding on a certain segment is influenced by factors related to multiple communities. When including community-level factors in the regression model, it is difficult to find the one-to-one relationship between community and road segment, which is known as the boundary problem (Siddiqui and Abdel-Aty, 2012, 2016; Zhai et al., 2018). The common method for this problem is to treat a road segment neighboring multiple communities as several segments with each segment corresponding to one community, and thus the conventional multilevel model (CMM) could be used (Cai et al., 2018; Chung and Beretvas, 2012; Pulugurtha and Sambhara, 2011; Wang and Huang, 2016). Recent research of Park et al. (2020) shows that the multiple membership multilevel model (MMMM) could deal with the boundary problem by assigning equal weight to communities adjacent to one segment. Therefore, we will use the MMMM in this study and compare the result with that of CMM.

The rest of this paper is organized as follows. In the second section, previous research related to this study is reviewed. Data and variables used in this study are described in Section 3. In the methodology section, the CMM and MMMM are introduced. In the results section, the outcome of the model is interpreted, and the performance of the MMMM is compared with that of the CMM. The last section presents the discussion and conclusion.

2. Literature review

2.1. ESS related studies

So far, studies related to the association between the link level ETV and the infrastructure design and land use patterns are still limited. Most of the existing studies focused on the factors that influence ESS usage in different areas (Aguilera-García et al., 2020; Bai and Jiao, 2020; Caspi et al., 2020; Hosseinzadeh et al., 2021a; Hosseinzadeh et al., 2021b; Huo et al., 2021; McKenzie, 2019). Some other studies analyzed the impact of the ESS on the usage of other transportation modes such as private car, bike sharing, and bus (Guo and Zhang, 2021; Yang et al., 2021; Ziedan et al., 2021). Other scholars have studied people's intention to choose ESS to travel (Aman et al., 2021; Eccarius and Lu, 2020; Gitelman et al., 2017; Sanders et al., 2020), and found that travelers considered the riding environment as important factors. But these studies did not point out specifically what type of road features were favored by e-scooter riders. So far, there have been a limited number of studies focusing on e-scooter users' preference of road attributes. These studies usually use route choice models to perform the analysis. Zou et al. (2020) analyzed the trajectory data of ESS trips which are extracted at the interval of 30s and found that the minor arterials, collectors, and local streets are the most popular facilities used by ESS, and if there are bicycle lanes on the streets, they will likely attract more e-scooter traffic. Zuniga-Garcia et al. (2021) analyzed the trajectory data of ESS trips and found that the average riding distance decreases when the scooters are ridden on the following three types of infrastructures: automobile lane, sidewalk, and bicycle lane. However, the road infrastructure analyzed in this study is somehow limited. Some important factors such as lighting and greening are omitted. Zhang et al. (2021) applied the Recursive Logit route choice model to study the features of infrastructures that e-scooter riders prefer. The results showed that ESS users prefer shorter and simpler routes. They also have higher willingness to ride in bikeways, multi-use paths, as well as one-way roads. However, the study area is only the Virginia Tech's campus. The results of this study not may be applicable to other places.

2.2. Studies related to route choice behavior of bicyclists

Route choice behavior is usually analyzed to explore the effects of the road environment on riders' choice of road segment or route. Since both e-scooter and bicycle belong to the category of micro-mobility, studies related to the route choice behavior of bicyclists are reviewed in this section to gain insights on what road features are more favored by riders.

First of all, distance is one of the most important environmental factors affecting route choices (Hood et al., 2011; Menghini et al., 2010; Stinson and Bhat, 2003). The change in terrain elevation is also a significant factor. Riding on a steeper slope requires more physical effort from cyclists (Broach et al., 2012). When there are motor vehicles traveling on the road, the size and speed of motor vehicles could affect the safety perception of cyclists (Stinson and Bhat, 2003; Tilahun et al., 2007). Various types of road infrastructure, such as bike path, road lights, bike facility signs, and markings, could all influence bicyclists' route choice (Dill et al., 2014; Monsere et al., 2014; Tilahun et al., 2007). It can be seen that road attributes could indeed influence bicyclists' choice of road segment, and these results could assist in designing more friendly roads for cyclists to provide a safer and more comfortable riding environment. These results are also helpful for designing e-scooter friendly roads.

2.3. Studies related to boundary problems

To study the influence of attributes of segments on ETV, it is necessary to control for the community-level attributes that also influence the ETV. When including those attributes in the model, the unobserved heterogeneity problem would arise because several road segments could fall within one community (Park et al., 2017; Raudenbush and Bryk, 2002). The multilevel model is widely used in transportation-related studies to deal with this problem (Ding and Cao, 2019; Gehrke, 2020; Hong and Goodchild, 2014; Iseki et al., 2018; Kim et al., 2014; Sabouri et al., 2020; Yang et al., 2021; Yang et al., 2022). On the other hand, since many segments are the common boundary of multiple communities, a boundary problem could also arise, which means that multiple communities are related to one road segment, and it is difficult to build a one-to-one relationship between community and road segment (Cai et al., 2018; Wang and Huang, 2016; Wang et al., 2017). A common practice is to aggregate the attributes of multiple adjacent communities to build a virtual community by giving weight to each community. Methods in these studies can be generally classified into four types: (1) Treat a road segment that is the boundary of multiple communities as several segments, each of which corresponds to one adjacent community (Park et al., 2020). This method would overweight the boundary road segment and thus lead to biased results. (2) Adopt a larger community to include as many analysis units with boundary problems as possible and choose a dominant community for the rest of the units with the problem (Cai et al., 2018). This method would reduce the sample size and it is easy to overlook the influence of some non-dominant communities on the analysis unit. (3) Determine the weight based on the geographic area of the community (Wang and Huang, 2016). This method weakens the influence of some communities with small geographic areas but high impact. (4) Draw a buffer area around the road segment as the catchment area (Wang et al., 2017). But the selection of buffer radius is usually arbitrary. So, all of these methods have some shortcomings. A recent study by Park et al. (2020) has shown that assigning equal weight to multiple communities adjacent to one segment could avoid overvaluing the effect of certain communities and could obtain better results. As a result, in this study, we adopt this method to deal with the boundary problem.

To sum up, the effects of road features on ETV are still not clear, which prohibits the appropriate design of related policies and regulations. In order to fill this gap, this paper employs a multilevel modeling approach to explore the effect of road segment attributes on the ETV of the segment while controlling for community-level attributes. The results of this study could provide a valuable reference to policymakers to determine what type of lane or road should e-scooters be ridden on.

3. Data

3.1. Study area

Calgary is located in the province of Alberta, western Canada. Its land area is about 825.56 km^2, and its population density is 1,501.1 persons/km^2. Calgary is also the third largest municipality in Canada (after Toronto and Montreal). With warm summers and cold, dry winters, the city was named the most livable city in North America in 2018 and 2019. The city currently operates two light rail lines and more than 160 bus lines. In October 2018, the government passed a two-year Shared Mobility Pilot to explore new ways of providing flexible, affordable and accessible mobility options. Since the launch of the pilot, there have been three permitted private sector operators (Lime, Bird Canada, and Roll) and 1.9 million shared mobility trips. The pilot provided that ESS are permitted to operate on the City's bicycle lanes and pathways and quiet sidewalks, and are not allowed to ride on busy roadways. The map of Calgary is shown in Fig. 1. The Calgary Transit system is made up of bus and light rail transit (LRT) (see Fig. 2).

3.2. Data description

The city of Calgary offers an open data platform that provides trip data of the ESS system, which is a two-year pilot program. The data includes departure and arrival time, trip starting and ending location (with the accuracy of about 1 m), and trip distance and duration. We downloaded the data on December 1st, 2019.[1] The time period of data used in this study is from July 1st to September 30th, 2019. The road segments with ESS trip records are obtained.[2] The ETV of each road segment is also provided by the dataset. In the original data, there were 29,585 road segments. We deleted 41 segments that are outside of the city. Thus, 29,544 road segments are left and used for this study. The total volume of e-scooter trips on these segments is 4,517,014.

3.2.1. Community-level factors

The selected community-level variables contain three categories: demographics, transportation infrastructure, and land use. The descriptive statistics of the selected variables are shown in Table 1.

3.2.2. Segment-level factors

The segment-level factors contain four categories: design, sidewalk, bikeway type, and roadway type. The descriptive statistics of the selected variables are shown in Table 2 and Table 3.

According to the classification published by the official website of the Calgary Municipal Government (Calgary, 2019a), bicycle facilities are divided into four categories. The first category, cycle track, is completely separated from the roadway and has designated signs and marking. It is the most exclusive type of bicycle facility for riding and thus provides riders with the most comfortable riding environment. The second category is the bicycle lane, which is set between the lanes of the opposite traffic, equipped with signs and markings. The third category is the shared way, on which bicycles share the lane with motor vehicles. But there are signs set up showing bicycles could be ridden in the lane. The fourth category is on-street bikeway. The main difference between on-street bikeway and shared way is that there are no signs showing bicycles could be ridden in the lane. Some segments, however, have no bike facilities, so they are represented by others. Fig. 3 shows the layout of each type of bicycle facility. If a motor vehicle's color is grey, it means parked, while black means moving.

According to Calgary's road classification standard (Calgary, 2019b), the roadway is divided into five types, ordered based roughly on Annual Average Daily Traffic (AADT) from high to low: skeletal roads, arterial street, prestige road, urban boulevard, and neighborhood boulevard. Skeletal Roads mainly refer to rapid roads in cities, with AADT exceeding 30,000 Passenger Car Unit per day (pcu/d). This type of road has a high traffic volume, and there are usually no sidewalks or bicycle facilities on the road. The arterial street is also a rapid road, with AADT ranging from 10,000 pcu/d to 30,000 pcu/d. It is the major component of the road network of a city. Usually, the bicycle lanes and sidewalks are physically separated from the roadway on the arterial by green belts and fences. The main role of the collector road is to connect the local street to the main street. Urban boulevard is an important part of the urban road network, which can directly connect to residential areas. The motor vehicles running on this type of road have a relatively low speed. At the same time, it is fully integrated with the adjacent mixed land use and has better access to the surrounding communities. Usually, these roads are designed with more emphasis on greenery, lighting, and so on. The neighborhood boulevard is similar to urban boulevard, which mainly connects to various communities. Walking and bike riding have priority on such roads. Road segments without motor vehicles, used only for residents or for special purposes, are uniformly indicated by others.

3.3. Data analysis

Fig. 4 shows the spatial distribution of the ESS trip origin in Calgary. It can be seen from the figure that ESS was used most frequently in the downtown area, and the farther away from the downtown, the lower the volume is. Although the central areas only occupy 10% of the total area of the city, about 90% of the trips originated from these areas. Studies from other cities drew similar conclusions (Caspi et al., 2020). Since the University of Calgary is not open to ESS during the study period, ESS usage is low in the university area, and thus segments in this area have been deleted.

The spatial distribution of road segments of different ETVs in Calgary is shown in Fig. 5. It can be seen that although the usage for ESS is high in the downtown area, the ETVs on different segments within the same region still differ.

To understand what type of road segment is used more frequently by e-scooter riders, we compare the proportion of a certain type of road segment to the total number of road segments with the proportion of ETV on this type of segment to total trip volume. We divide the latter proportion by the former proportion to get an index, which is called the utilization rate. When the rate is higher than 1, it means that the proportion of ETV on this type of road segment is higher than the proportion of this type of segment to the total number of segments, which indicates this type of road segment is favored by e-scooter riders. A higher value of the utilization rate indicates the type of road segment is more favored by riders. The results are shown in Table 4. We can see that in terms of bikeway and roadway type, segments with cycle track and neighborhood boulevard have the highest utilization rates, around 22.250 and 6.534, respectively. Regarding whether there is a sidewalk on the road segment, it can be seen that the utilization rate of road segments with a sidewalk is much higher than that of segments without a sidewalk.

The numbers of trips of different trip distances (with an interval of 0.1 km) and detour ratios (with an interval of 0.1) are shown in Fig. 6. The detour ratio is calculated as the ratio of trip distance divided by the straight-line distance between origin and destination. It can be seen

[1] https://data.calgary.ca/Transportation-Transit/Shared-Mobility-Pilot-Trips/jicz-mxiz.

[2] https://data.calgary.ca/Transportation-Transit/Shared-Mobility-Pilot-Trip-Segment-Counts/75pg-pxz2.

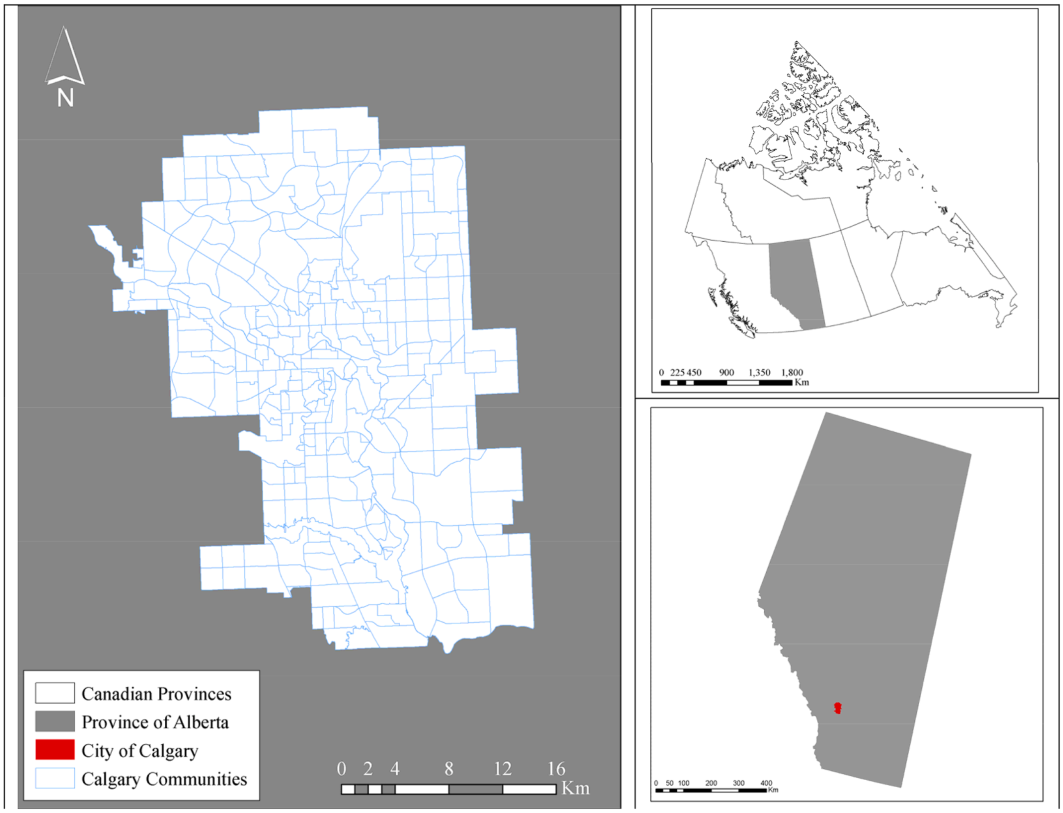

Fig. 1. Study area: City of Calgary (left); Canadian provinces (top right); Province of Alberta (bottom right).

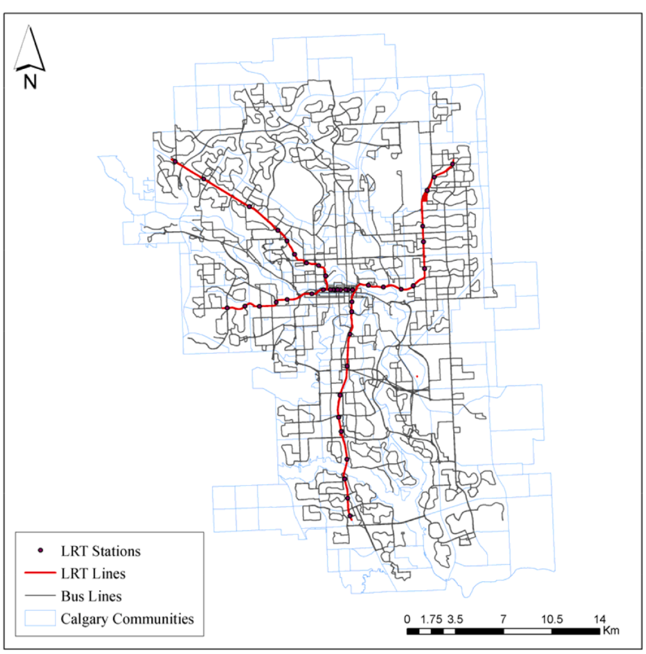

Fig. 2. Public transportation facilities in Calgary.

from Fig. 6 that the trip distance and detour ratio of ESS trips mostly range from 0 to 4 km and 1–3, respectively. It can be seen that the ESS is usually used for short-distance travel.

4. Methodology

This section describes the models that will be used in this study. First, the variance partition coefficient (VPC), which is the variance at a given level of the model divided by the total variance, is used to determine whether the multilevel modeling approach should be adopted. In this study, it can be regarded as the proportion of variance explained by the community-level model. A higher value of VPC indicates the multilevel model is more suitable. The research results showed that when the VPC was greater than 0.05 (5%) (Browne et al., 2005; Goldstein et al., 2002; Yoon et al., 2017), a multilevel model should be used. We used the method proposed by Browne et al. (2005) to calculate the VPC value.

$$VPC = \sigma_u^2/(\sigma_e^2 + \sigma_u^2) \tag{1}$$

where σ_u^2 is variance at the community level, and σ_e^2 is variance at the road segment level.

4.1. Conventional multilevel model

Equation (2) is a two-level model that considers the fact that many road segments fall within one community (Raudenbush and Bryk, 2002). In the model, the road segment is set to be the first level, and the community is set to be the second level.

$$\begin{aligned} Y_{ij} &= \beta_{0j} + \sum_{p=1}^{P} \beta_{pj} X_{pij} + e_{ij}(Level1) \\ \beta_{0j} &= \gamma_{00} + \sum_{q=1}^{Q} \gamma_{0_q} Z_{qj} + u_{ij}(Level2) \\ & e_{ij} hN\left(0, \sigma_e^2\right) u_{ij} hN\left(0, \sigma_u^2\right) \end{aligned} \tag{2}$$

On the segment level (level 1), Y_{ij} represents the ETV on road segment i in community j. X_{pij} represents attribute p of road segment i in community j. β_{pj} represents the regression coefficient. e_{ij} is the error term or residual that is assumed to follow the normal distribution. On the community-level (level 2), β_{0j} is the random intercept of the segment-

Table 1
Descriptive statistics for community-level factors.

Type	Factors	Definition	Min.	Max.	Mean	S.D.
Demographics	Income	Median income	9,866.124	103,581	42,022.466	16,776.471
Transportation infrastructure	Population density	Persons per square kilometer	342.590	12,195.363	2,730.32	1,498.580
	Employment density	Jobs per square kilometer	18.548	8,769.063	1,422.364	911.830
	Road density	Road length per square kilometers	6.994	63,368.290	19,436.450	8,307.956
	Transit density	Bus and LRT stops per square kilometer	0	60.123	34.1321	12.099
	Intersection density	Intersections per square kilometer	0	5.213	2.435	0.853
Land use	Commercial Core	Percentage of commercial area	0	0.800	0.005	0.064
	Commercial	Percentage of commercial area	0	0.464	0.040	0.062
	Residential density	Percentage of residential area	0	0.734	0.071	0.078
	Industrial	Percentage of industrial area	0	0.873	0.035	0.141
	Institutional	Percentage of institutional area	0	0.956	0.035	0.184
	Park	Percentage of park area	0	0.754	0.120	0.456

Table 2
Descriptive statistics of segments-level factors.

Type	Factor	Definition	Min.	Max.	Mean	S.D.
Design	Elevation	Road segment elevation (m)	1,007.786	1,258.088	1,106.541	43.516
	Speed	Speed limit for motor vehicle	30	110	39.547	12.169
	Distance	The distance from the segment center to the city center	0	22,596.640	7,846.935	4,496.142
	Trees density	Number of trees along the road segment per kilometer	0	31.299	0.298	27.38
	Lights density	Number of street lights along the road segment per kilometer	0	12.835	0.057	4.025
	Intersection	If the road segment connects to an intersection = 1, otherwise = 0	0	1	–	–
Sidewalk	Sidewalk	If the road segment has sidewalk = 1, others = 0	0	1	–	–
Bikeway type	Bikeway type	On-street Bikeway = 4, Shared way = 3, Bicycle lanes = 2, Cycle tracks = 1, others = 0	0	4	–	–
Roadway type	Roadway type	Neighborhood boulevard = 5, Urban boulevard = 4, Collector = 3, Arterials road = 2, Skeletal roads = 1, others = 0	0	5	–	–

Table 3
Descriptive statistics of the discrete variables.

Factor	Level	Segment Number	Segment proportion
Intersection	The road segment connects to an intersection	7,447	0.252
	Others	22,097	0.748
Bikeway	Cycle tracks	109	0.004
	Shared Lane	612	0.021
	Bicycle Lane	400	0.012
	On-Street Bikeway	3,099	0.106
	Others	25,324	0.857
Roadway	Skeletal roads	326	0.011
	Arterials roads	2,466	0.083
	Collectors	8,047	0.272
	Urban boulevard	643	0.022
	Neighborhood boulevard	364	0.012
	Others	17,698	0.599
Sidewalk	The road segment has sidewalk	9,134	0.309
	Others	20,410	0.691

level model that is determined by the attributes of the community. Z_{qj} represents the explanatory variable q for community j. γ_{0q} represents the regression coefficient for Z_{qj}. u_{ij} is the error term or residual of the second level that is also assumed to follow the normal distribution. The residual of Y_{ij} is divided into two parts, e_{ij} and u_{ij}. These two parts of the residual are used to compare the relative influence of variables of the first and second levels on $Y_{ij.}$

However, some road segments are at the boundary of multiple communities, and cannot be simply regarded as falling within a single community. As a result, MMMM is used to deal with this problem and is described below.

4.2. Multiple membership multilevel model

Equation (3) is the mathematical expression of the MMMM. In the model, the intercept term of the second level represents the influence of multiple communities.

$$Y_{ij} = \beta_{0j} + \sum_{p=1}^{P} \beta_{pj} X_{pij} + e_{ij}(level1)$$

$$\beta_{0j} = \gamma_{00} + \sum_{q=1}^{Q} \gamma_{0q} \sum j \in Com(i) w_{ij} Z_{qj} + \sum j \in Com(i) w_{ij} u_{ij}(level2) \quad (3)$$

$$e_{ij} h N\left(0, \sigma_e^2\right) u_{ij} h N\left(0, \sigma_u^2\right)$$

In Eq. (3), $\sum_{q=1}^{Q} \gamma_{0q} \sum_{j \in Com(i)} w_{ij} Z_{qj}$ is the fixed part of the model, which is the sum of the product of the weighted sum of community-level influencing factors and corresponding regression coefficient; The random part of the model,$\sum_{j \in Com(i)} w_{ij} u_{ij}$, is the weighted sum of random effects of the second level. The sum of the weights is equal to $1\left(\sum_{j \in Com(i)} w_{ij} = 1\right)$. In this study, equal weight is used, as suggested by Park et al. (2020).

5. Results

Before modeling, we calculated correlation coefficients to detect the multicollinearity of variables. According to previous research, variables with correlation coefficients greater than 0.5 or lower than −0.5 are considered highly correlated (Rose and Hensher, 2014). Since we use many socioeconomic and built environment variables, some of them are highly related (Yang et al., 2022; Yang et al., 2022). For example, the correlation coefficient between population density and employment density and that of population density and road density are higher than 0.6, and thus employment density and road density variables are deleted.

The dependent variable is the cumulative ETV for three months on each road segment, which is a count variable. We performed a natural logarithmic transformation on the dependent variable to make it roughly follow the normal distribution, which is a common practice and is also used to study the ESS usage in Austin by Caspi et al. (2020). Both MMMM and CMM were fitted using MLwiN software and the Bayesian

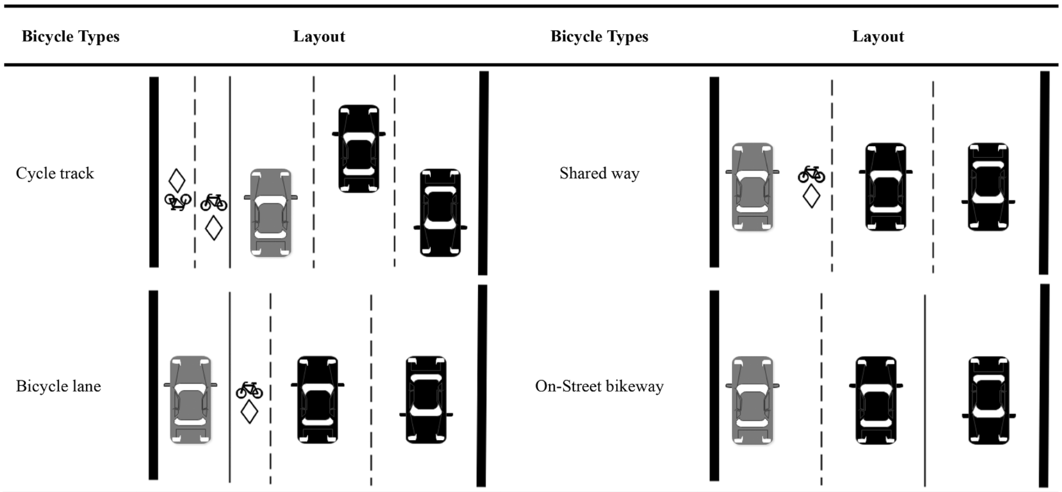

Fig. 3. Layout of bikeway facilities.

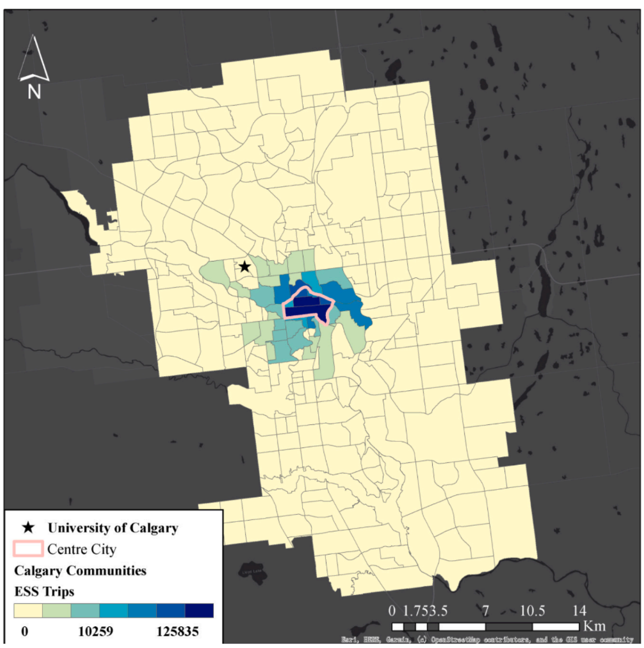

Fig. 4. Spatial distribution of ESS usage in Calgary.

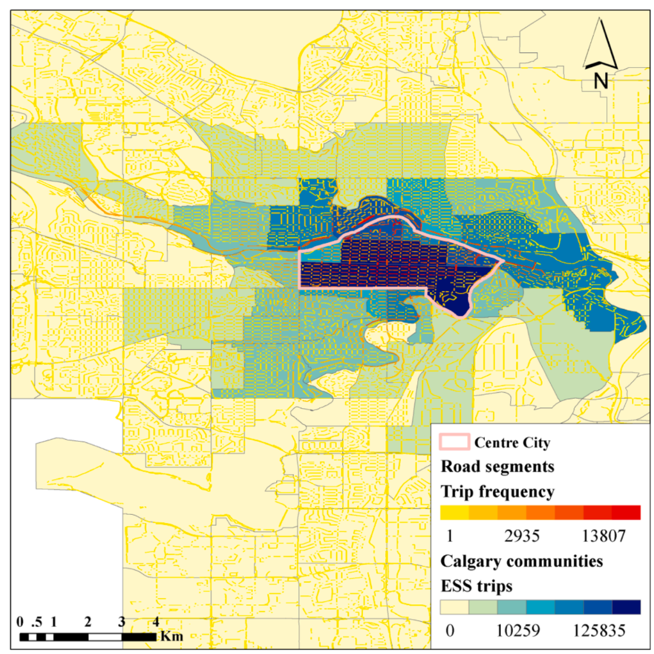

Fig. 5. ETV on segments of road in Calgary.

MCMC parameter estimation method (Browne, 2014; Browne et al., 2001; Yang et al., 1999). In each model, we used a burn-in of 1000 iterations and a monitoring chain of 20,000 iterations. The results of the two models were compared.

Table 5 compares the community-level variance, segment-level variance, and VPC of CMM and MMMM. The VPC values of the two models are both higher than 0.05. It shows that the multilevel model is more suitable for our research than the single-level model.

The Deviance Information Criterion, a likelihood-based measure for comparing non-nested multilevel models (DIC), is used to quantitatively evaluate performance between the MMMM model with CMM, which is consistent with other studies (Park et al., 2020; Stinson and Bhat, 2003). The results are shown in Table 6, which includes factors that are statistically significant at the 10% level. It can be seen that MMMM has a smaller DIC value compared to CMM, which shows that MMMM fits the data better. The interpretation of the model results is shown below.

5.1. *Segment-level factors*

5.1.1. *Road design*

From the modeling results, we can see a negative correlation between the altitude of the road segment and ETV, which shows that although the e-scooter is electric powered, the users are still unwilling to ride to segments of higher elevation by climbing up the hill. In terms of the surrounding environment of the road, there is a positive correlation between the ETV and the density of trees as well as the density of street lights along the road segment. This finding is consistent with previous studies indicating that the degree of green surrounding the road could improve residents' travel experience from a visual perspective (by providing shades, and the setting of street lights could improve the sight distance and safety of riding at night) (Park and Akar, 2019). In addition, we also analyze the impact of connecting to an intersection on the ETV of the road segment, and the results show that there is a positive correlation between the two. The study of Caspi et al. (2020) also drew similar conclusions. It shows that the accessibility provided by

Table 4
Utilization rate of road segment attributes.

Type	Factor	Segment Number	Segment proportion[1]	ETV	Volume proportion[2]	Volume proportion / Segment proportion
Bikeway	Cycle tracks	109	0.004	400,259	0.089	22.250
	Shared Lane	612	0.021	305,193	0.068	3.238
	Bicycle Lane	400	0.012	96,865	0.021	1.750
	On-Street Bikeway	3,099	0.106	459,236	0.102	0.962
	Others	25,324	0.857	3,255,461	0.720	0.840
Roadway	Skeletal roads	326	0.011	6,482	0.001	0.130
	Arterials roads	2,466	0.083	514,802	0.114	1.365
	Collectors	8,047	0.272	975,235	0.216	0.793
	Urban boulevard	643	0.022	593,020	0.131	6.032
	Neighborhood boulevard	364	0.012	363,632	0.081	6.534
	Others	17,698	0.599	2,063,843	0.457	0.763
Sidewalk	Sidewalk	9,134	0.309	3,349,840	0.742	2.399
	Others	20,410	0.691	1,167,174	0.258	0.373

[1] Segment proportion: The ratio of the number of road segments with this attribute to the total number of road segments (29,544).
[2] vol proportion: The ratio of the ETV on this type of road segment to the total ETV (4,517,014).

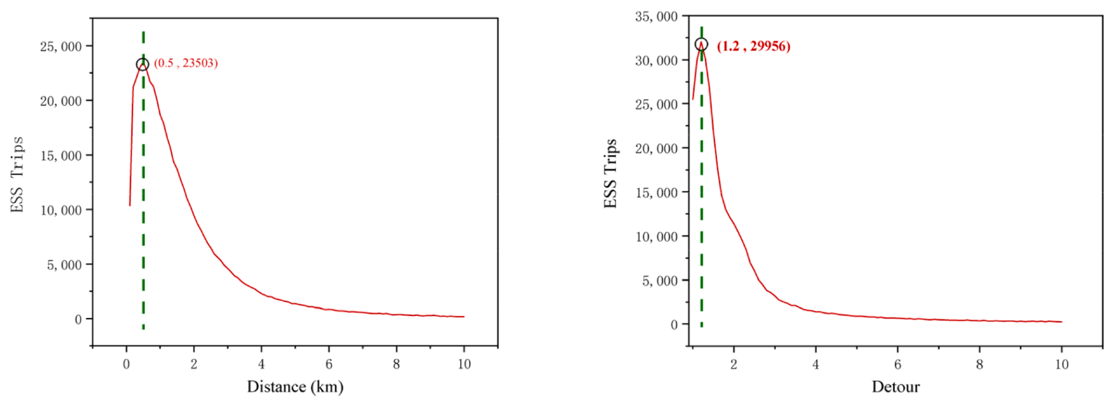

Fig. 6. Number of trips of different trip distances and detour ratios.

Table 5
Variance of the community level and segment level.

	CMM	MMMM
Community-level Variance	0.165	0.196
Segment-level Variance	0.125	0.118
VPC	0.635	0.734

connecting to an intersection in terms of allowing e-scooter riders to go straight, turn right, or turn left is more important than the possible delay caused by the traffic light at the intersection. There is a negative correlation between the speed limit of motor vehicles of the road segment and ETV. A higher speed limit is related to higher traffic speed, which could potentially increase the severity of traffic accidents and thus reduces the willingness of e-scooter users to ride on this type of segment. Regarding the relationship between the distance from the center of the road segment to the city center and the ETV of a segment, the results show that there is a negative correlation, which indicates the segments closer to the city center have a higher ETV.

5.1.2. Bikeway

We find that different types of bikeways are favored differently by e-scooter riders. Firstly, we show that compared with other types of bicycle lanes, the coefficient of the variable cycle track is the highest, which means that the exclusive right of way is important and attractive to e-scooter riders. A segment with a cycle track is associated with an increase of 46% of ETV compared to segments without such a track. This is consistent with the results of previous studies that have shown that dedicated bicycle lanes have the highest safety level among multiple types of bicycle facilities (Apasnore et al., 2017; Debnath et al., 2018). Secondly, the existence of bicycle lanes on the road segment could significantly increase the ETV of the segment. This verifies the results of previous studies that the density of bicycle lanes in the community is positively related to ESS demand (Caspi et al., 2020). Thirdly, compared with the type of other, the on-street bikeway is also positively related to ETV, although the value of the coefficient is lower than those of the previous two types. At last, the shared way could also increase the ETV of the road segment. The values of coefficients of the four types of bicycle facilities correspond to how exclusive the facility is, with a higher value corresponding to a more exclusive facility.

5.1.3. Roadway

Modeling results show that compared with other road types, neighborhood boulevard has the highest coefficient, which indicates it is the most favored roadway of e-scooter riders. This is probably because neighborhood boulevard provides riders and pedestrians the highest right-of-way, with a safe and comfortable riding environment, which is very suitable for e-scooters to be ridden on. Research on the route choice of bicyclists also found that a relatively complete bike infrastructure could improve the cyclist's riding experience (Stinson and Bhat, 2003). The second road type, urban boulevard, is also related to high ETV. Although this type of road has a higher traffic volume, the speed of traffic is relatively low, and pedestrians and cyclists still have a relatively high right of way. The arterials roads and collectors are also positively related to ETV, indicating these road segments are more favored than the reference road type, others. But they are not as attractive as neighborhood boulevards and urban boulevards.

5.1.4. Sidewalk

We find that road segments with sidewalks are related to higher ETV,

Table 6
Model Results.

			Conventional multilevel model			Multiple membership multilevel model		
			Coef.	Std. Dev.	p	Coef.	Std. Dev.	p
	(Intercept)	3.863	0.283	<0.001	2.982	0.291	<0.001	
Community-level	Density	Population density	4.81E-05	1.75E-05	0.006	4.87E-05	1.88E-05	0.006
		Transit density				0.002	4.07E-04	<0.001
		Intersection density				0.001	1.87E-04	<0.001
	Demographics	Median income				4.77E-06	1.50E-05	<0.001
	Land use	Residential	0.019	0.006	<0.001	0.014	0.003	<0.001
		Commercial				0.817	0.149	<0.001
		Commercial-Core	1.211	0.558	0.030	0.985	0.125	<0.001
		Industrial	−0.790	0.162	<0.001	−0.106	0.068	0.050
		Park	0.223	0.007	<0.001	0.212	0.007	<0.001
Segments-level	Road design	Trees density	0.001	1.36E-04	<0.001	0.001	1.42E-04	<0.001
		Lights density	0.007	0.001	<0.001	0.006	0.001	<0.001
		Elevation	−0.002	2.47E-04	<0.001	−0.001	2.74E-04	<0.001
		Distance	−1.43E-04	2.96E-06	<0.001	−1.32E-04	3.07E-06	<0.001
		Intersection	0.029	0.005	<0.001	0.037	0.006	<0.001
		Speed	−0.004	0.001	<0.001	−0.003	4.24E-04	<0.001
	Bikeway	Bikeway- Other	Reference					
		Cycle tracks	0.386	0.035	<0.001	0.372	0.035	<0.001
		Bicycle lane	0.338	0.014	<0.001	0.327	0.015	<0.001
		Shared way	0.329	0.024	<0.001	0.301	0.026	<0.001
		On-Street Bikeway	0.142	0.007	<0.001	0.135	0.007	<0.001
	Roadway	Road Type- Other	Reference					
		Skeletal roads						
		Arterials roads	0.169	0.012	<0.001	0.174	0.013	<0.001
		Collectors	0.201	0.009	<0.001	0.206	0.010	<0.001
		Urban boulevard	0.342	0.015	<0.001	0.335	0.018	<0.001
		Neighborhood boulevard	0.511	0.018	<0.001	0.445	0.021	<0.001
	Sidewalk	Sidewalk	0.084	0.005	<0.001	0.069	0.005	<0.001
Random-effects Parameters								
	Var(cons)-community-level	0.192	0.017	<0.001	0.198	0.019	<0.001	
	Var(cons)-segment-level	0.128	0.001	<0.001	0.119	0.001	<0.001	
	Measures for Model Evaluation							
DIC			26204.04			21339.97		

which means that e-scooters tend to be ridden on road segments with sidewalks even after controlling for other variables. It shows that the sidewalk could provide a more comfortable riding environment. However, riding an e-scooter on the sidewalk would inevitably lead to interference with pedestrians, which may cause safety issues. In particular, vulnerable road users such as the elderly, children, and pedestrians with limited mobility are often at a disadvantage when encountering e-scooters, which are usually ridden at high speed (Sikka et al., 2019).

5.2. Community-level factors

For community-level variables, it can be seen from Table 5 that there is a positive correlation between population density and the number of e-scooter trips of the road segment, consistent with the study of (Bai and Jiao, 2020). Regarding income, the results show a positive correlation between the number of e-scooter trips and the median income of residents in the community. This is different from the study of Caspi et al. (2020), which found that the relationship between the median income of residents in the community and e-scooter trips was not significant in Austin. More research should be performed to investigate the relationship between e-scooter usage and the income of local residents to clarify the relationship. Regarding the relationship between e-scooter usage and public transit ridership, it is found that ETV is positively related to the density of bus stops and LRT stations in the surrounding community. This shows that ESS could be used as one of the tools to solve the "last mile problem" of transit.

Regarding land use, model results show that the ETV is positively correlated with the land use type of commercial core. Since the commercial core is located in the downtown area of Calgary, this finding is consistent with previous research that revealed shared e-scooters were mainly ridden in the central business district and downtown area (Bai and Jiao, 2020; Caspi et al., 2020). At the same time, the land use of residential and commercial is also positively related to e-scooter usage. The correlation between the land use of public institutions and ETV is not significant, while the correlation between industrial land use and ETV is negative. There are similar conclusions in the study of Caspi et al. (2020). The land-use type of park has a positive correlation with ETV. There are two possible reasons. Firstly, the e-scooter is sometimes ridden for entertainment and thus is ridden in parks. Secondly, there are pathways in parks that are separated from motor vehicles, and e-scooters could be ridden on those parkways safely and comfortably. Bai and Jiao (2020) also found that ESS was more concentrated in recreational areas or park areas, which is consistent with our findings.

6. Discussion and conclusions

Since the advent of ESS, it has raised a lot of debate about what type of road infrastructure e-scooter should be ridden on, its speed limit, safety performance, and its impact on other modes of transportation. Previous studies usually focused on exploring the spatial variation of ESS demand at the community or zone level and analyzed the impact of regional socioeconomic and built environment factors on ESS ridership. While these studies provide guidance on how to determine the high-demand area and how the change of built environment could influence ESS ridership, they provide few insights on what type of road infrastructure e-scooters should be ridden on. This information is important when designing the appropriate infrastructure for e-scooter riders or making policies regulating what type of lane e-scooters should be ridden on.

In this paper, we analyze how road environment factors influence the ETV of the road segment. The multilevel modeling approach is used to deal with the heterogeneity problem caused by the fact that multiple road segments fall within one community. Besides, because some road segments are boundaries of multiple communities, which causes the boundary problem, the MMMM is used to deal with this problem by assigning equal weight to communities that are neighboring to the same road segment.

As in many cases, e-scooters are treated as bicycles and are allowed to be ridden in the same infrastructures as bicycles. So, we can explore whether e-scooters and bicycle riders share the same road environment preference, which is beneficial to the design of the regulation rule for the two modes. By analyzing the impact of attributes of road segments on ETV, we found that the density of trees and the density of street lights of the road segment are positively related to the ETV. The segments with exclusive bicycle facilities are usually associated with higher ETV. Not only the category of the roadway but also the speed limit of the road segment influence ETV: e-scooter is less ridden on road segments with high traffic volume and high vehicle speed. There is also a significant positive correlation between the existence of sidewalks and ETV. Regarding the road facility preference of bicyclists, previous studies showed that bicyclists prefer to ride on road segments with more exclusive facilities (e.g. paths or cycle tracks), lower vehicle speed, and lower traffic volume (Buehler and Dill, 2016; Hood et al., 2011; Rose and Marfurt, 2007; Winters and Teschke, 2010). It shows that e-scooter users and bicyclists have similar preference on roadway facilities. Moreover, modeling results at the community level show that the ETV is positively related to the density of bus stops and LRT stations in the surrounding community, which indicates that e-scooters could serve as a transfer mode for transit to solve the “last mile problem”, just as a bicycle. These conclusions, to a certain extent, indicate that bicyclists and e-scooter riders have a similar preference on the road environment.

The study also has a few limitations. First of all, limited by the cross-sectional research design, the relationship between the ETV of the road segment and attributes of the segment that we identified should be regarded as correlation instead of causality. Future research should use longitudinal data to delve deeper into the topic and reach a more persuasive conclusion. Another way to investigate this topic is to construct the route choice model to explore how road features influence e-scooter riders’ choice of the route that is composed of multiple road segments. This type of study could potentially provide more insights into this topic. Despite these limitations, this study is still one of the first studies that try to uncover the road features that are favored by e-scooter riders and could provide a glowing reference for transportation engineers to design road infrastructure that is more friendly to e-scooter users and for government agencies to determine what type of road or lane that e-scooters should be ridden on.

CRediT authorship contribution statement

Hongtai Yang: Conceptualization, Methodology, Writing – review & editing, Supervision. **Yongxing Bao:** Methodology, Formal analysis, Writing – original draft. **Jinghai Huo:** Methodology, Formal analysis, Writing – original draft. **Simon Hu:** Conceptualization, Methodology, Writing – review & editing, Supervision. **Linchuan Yang:** Conceptualization, Methodology, Writing – review & editing, Supervision. **Lijun Sun:** Conceptualization, Methodology, Writing – review & editing, Supervision.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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