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Influence of the built environment on *E*-scooter sharing ridership: A tale of five cities

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ABSTRACT

Electric scooter (e-scooter) sharing systems (ESSs) have been widely adopted by many cities around the world and have attracted a growing number of users. Although some studies have explored the usage characteristics and effects of the built environment on ESS ridership using one city as an example, few studies have considered multiple cities to obtain generalizable and robust results. To fill this research gap, we collect the ESS trip data of five cities in the U.S., namely Austin, Minneapolis, Kansas City, Louisville, and Portland, and explore the effects of the built environment on ESS ridership after controlling for socioeconomic factors. The temporal distributions of e-scooter ridership of different cities are similar, having a single peak period on weekdays and weekends between 11:30 and 17:30. In terms of spatial distribution, the ESS ridership is higher in universities and urban centers compared to other areas. Multilevel negative binomial model results show that ESS trips are positively correlated with population density, employment density, intersection density, land use mixed entropy, and bus stop density in the census block group. *E*-scooter ridership is negatively correlated with the median age of the population in the census block group and distance to the city center. The findings in this article can help operators understand the factors that affect the ridership of shared e-scooters, determine the changes in ridership when the built environment changes, and identify high-ridership areas when ESS is implemented in new cities.

1. Introduction

The e-scooter sharing system (ESS) is a new type of shared micro-mobility (Shaheen and Cohen, 2019). Compared with bicycles, e-scooters have electric power and higher flexibility and are leading a "micro-transportation revolution" (Aguilera-García et al., 2020; Zhu et al., 2020). ESS was first implemented in Los Angeles, U.S., in 2017 and then expanded to 115 cities in the U.S. The U.S. shared micromobility report shows that shared e-scooters have replaced shared bike to become the most favorable micromobility vehicles in 2018: 38.5 million ESS trips are reported compared with 9 million dockless bike sharing trips and 36.5 million station-based bike sharing trips (NACTO, 2019). A dockless scheme is usually adopted, indicating that shared e-scooters can be parked at any places deemed appropriate in the designated operation area (Guo et al., 2020). Many ESS programs publish e-scooter trip data on their website, making it available for research purposes.

Although some studies have investigated the effect of the built environment on ESS ridership (Bai and Jiao, 2020; Caspi et al., 2020; Hosseinzadeh et al., 2020, 2021a; Jiao and Bai, 2020), they are usually based on data from one or two cities. The limitations of these studies are that (1) the results are bound by the urban settings of that city so that the transferability of the results is doubtful, and (2) the sample size is usually limited due to the small ESS operating area of the city, so the analysis results may not be reliable. To address these issues, this study pools the ESS ridership data of five cities (Austin, Minneapolis, Kansas City, Louisville, and Portland) in the U.S. into one data set so that the results obtained from analyzing this data set are more transferable and reliable. Since most multiple-city studies analyzed three to six cities (Duran-Rodas et al., 2019; Gehrke, 2020), data of five cities is enough to demonstrate our contribution. We adopt the same set of the built environmental variables for the five cities. A multilevel modeling approach is used in this study to capture the nested data structure because CBGs

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are nested within the city.

Different from existing research, we use the ridership per unit area of each census block group (CBG) as the dependent variable rather than the total number of trips. There are two reasons for using ridership per unit area as the dependent variable. Firstly, when the ridership of a CBG is used as the dependent variable, the results would be interpreted as when an explanatory variable such as population density increases by one unit, the ridership of a CBG increases by β_x. This interpretation is ambiguous because the area of the CBG is not given. At least, it is not as clear as the following interpretation: when an explanatory variable such as population density increases by one unit, the ridership per unit area increases by β_x. Secondly, the area of a CBG is highly positively related to the distance between the CBG and the city center. When including the area of a CBG in the model, its coefficient could possibly be negative, indicating that the area of a CBG is negatively related to the ridership, which is misleading. Using ridership per unit area as the response variable could avoid this misleading result.

The remainder of this paper is organized as follows. The next section reviews the existing studies on e-scooter trips and studies analyzing the transportation system of multiple cities. The third section describes the data used in the study and the multilevel mixed-effect negative binomial regression model. The fourth section discusses the data analysis and model results. The fifth section provides the conclusions and suggestions for future research.

2. Literature review

2.1. E-scooter related studies

The initial research related to ESS mainly uses news reports or video data to analyze the influence of shared e-scooters on the urban transportation system. Gössling (2020) collected news via the Internet ($n = 173$) to assess the challenges faced by 10 cities when launching the ESS program. He suggested that city planners should set speed limits, require mandatory use of e-scooter infrastructure, design dedicated parking spaces, and limit the number of licensed operators. Tuncer et al. (2020) used video data to investigate the behavior of ESS users in public space and described their interaction with pedestrians. Brown et al. (2020) investigated the parking practices and the frequency and types of parking violations of three types of vehicles, e-scooters, bicycles, and motor vehicles. They found that motor vehicles violated the parking policy more often (24.7%) than bicycles (0.3%) and e-scooters (1.7%). Fitt and Curl (2020) found that the advent of ESS might challenge the existing urban structure, and some people did not think that e-scooter should be used in existing urban environments.

Other studies collected data using questionnaire surveys to investigate e-scooter users or potential users' intention and behavior. Eccarius and Lu (2020) collected questionnaires from 471 college students in Taiwan and analyzed the intentions of college students to use ESS. The results showed that the e-scooter usage characteristics differed among students of different majors. A study in Israel found that for the elderly users, e-scooters could serve as a promising alternative transportation mode and that e-scooters' movement on a sidewalk did not create conflicts with pedestrians, whereas the movement in the motor vehicle lane sometimes disturbed vehicle flows and created dangerous situations. Aguilera-García et al. (2020) studied the factors influencing people's choice to use e-scooter sharing by performing a questionnaire survey and found that social demographics, such as age and education level, significantly affected e-scooter trips. Laa and Leth (2020) found that in Vienna, e-scooter users, including e-scooter owners and ESS members, were more likely to be young, male, educated, and more likely to be Vienna citizens.

Several subsequent studies relied on publicly available shared e-scooter data. Some studies compared the determinants of temporal trips of the ESS and bike sharing in Washington, DC (McKenzie, 2019; Younes et al., 2020). They found that the use of ESS had a competitive relationship with the use of bike sharing by nonmembers and a complementary relationship with the use of bike sharing by members. They also found a positive correlation between the usage of all types of micromobility and gasoline prices. Many researchers focused on the effect of the built environment on the ESS ridership (Bai and Jiao, 2020; Caspi et al., 2020; Hosseinzadeh et al., 2020; Jiao and Bai, 2020). They found that ESS was mostly used for short-distance trips, and commuting was not the main trip purpose. Regarding the spatial distribution of trips and the effect of the built environment, these studies showed that ESS was mostly used in the downtown area and universities. High employment rate, complete bicycle infrastructure, and high accessibility to public transit were all positively related to ESS trips. These studies also had some different findings. Commercial areas were positively related to e-scooter trips in Austin and Louisville, but not in Minneapolis. The percentage of park area was positively related to e-scooter trips in Austin, but not in Louisville and Minneapolis. Some findings, such as the negative relationship between the proportion of young residents and the e-scooter usage, were counterintuitive (Jiao and Bai, 2020). Thus, their findings might not be transferable to other cities, thereby calling for more generalizable findings.

2.2. Study of multiple cities

In terms of multicity comparative study, the transportation modes analyzed include ridesourcing, bike sharing, ESS, and transit.

Regarding ride-sourcing, researchers used a multilevel model to analyze how the demand for Ubers is affected by the built environment based on the data of 24 regions in the U.S. (Sabouri et al., 2020). Gehrke (2020) quantified the continuous expansion of the outlying communities of Uber ride-hailing service from 2016 to 2018, used a multilevel model to identify the influence of the socioeconomic and built environment characteristics on the expansion of Uber.

The bike sharing services in many cities were compared, and the factors affecting the operation performance of the bike sharing system were analyzed (de Chardon et al., 2017; Duran-Rodas et al., 2019; Galway et al., 2021; Han, 2020; Hosford and Winters, 2018). de Chardon et al. (2017) studied the daily trips of bike sharing programs in 75 cities. They adopted a robust regression model to explore the influence of station density, weather, transportation infrastructure, and system-related characteristics on the performance of the bike sharing system. Duran-Rodas et al. (2019) combined the bike sharing data of multiple urban bike stations and used machine learning methods to analyze the data. Hosford and Winters (2018) summarized the bike sharing systems of five cities in Canada and analyzed the spatial equity of access to bike sharing. They used the Pampalon Deprivation Index to measure the socioeconomic status of each region and compared the spatial equity of access to bike sharing in different cities. For ESS, Bai and Jiao (2020) used a negative binomial regression model to analyze the influence of the built environment on the ridership of e-scooter and compared the influence in two cities: Minneapolis and Austin. In addition to the number of cities considered, the difference between that study and this one is that they analyzed the data of two cities individually, and the results are still specific to the studied city.

Some studies analyzed the impact of the built environment and gasoline prices on residents' choice of public transportation based on data of several cities (Diab et al., 2020; Lane, 2010; Sharma et al., 2020). Diab et al. (2020) collected the travel data sets of 103 Canadian transportation agencies from 2002 to 2016 and analyzed the relationship between Canadian transit demand and the built environment. They found that the factors affecting the ridership varied with the size of the public transportation agency. Lane (2010) analyzed the impact of rising gasoline prices on the number of public transit trips between August 2005 and July 2008. They found that changes in gasoline prices had a small but statistically significant effect on ridership.

While the abovementioned studies are usually based on data generated by the system, many studies collected data through questionnaire surveys. Guerra et al. (2020) collected survey data from the 100 largest cities in the United States and Mexico to compare the personal characteristics of people who used bicycles for commuting in different cities. The results showed that in the United States, the typical bicycle commuters were fresh graduates who lived in medium- and high-density cities and worked in the service industry with low salaries. Mexican bicycle commuters were low-income population, who were likely to work in agriculture, manufacturing industry, and were usually older. Kutela and Teng (2019) collected the bike sharing trip data of 24 universities in the United States and analyzed the effect of university characteristics, temporal factors, and weather on bike sharing trips. Two models, namelystandard negative binomial regression model and mixed-effects negative binomial regression model, were used. The mixed-effects negative binomial regression model had better goodness of fit. Aguilera-García et al. (2020) collected 430 samples to study the factors affecting the use of moped scooter-sharing in Spanish urban areas. They found that socioeconomic and travel-related variables affected the use of moped scooter-sharing significantly, whereas personal opinion and attitude were unimportant.

To the best of our knowledge, no studies have analyzed the effect of the built environment on ESS ridership based on data from multiple cities. Existing studies are usually based on one or two cities (Bai and Jiao, 2020; Caspi et al., 2020; Jiao and Bai, 2020; Liu et al., 2019; McKenzie, 2019; Noland, 2019; Orr et al., 2019) and model the trip data of different cities individually. These studies suffer from the two following limitations. First, although these studies can obtain results that are specific to the city, they cannot obtain generalizable or universal findings. Whether the findings of these studies can be applied to other cities is unclear. Second, the number of samples, which is usually the number of census tracts or CBG in the operation area, is low. A small sample size can possibly influence the reliability of the results. This study tries to analyze the ESS trip data of five cities in one model to obtain reliable and generalizable findings.

3. Research design

3.1. Study area and data source

The ESS trip data was obtained from the open data websites of the five cities: Austin (Austin Scooter, 2018), Minneapolis (Minneapolis Scooter, 2018), Louisville (Louisville Scooter, 2019), Kansas City (Kansas City Scooter, 2019), and Portland (Portland Scooter, 2019). The data includes trip ID, coordinates of OD, date, time, trip duration, and trip distance. Because the five cities provide e-scooter trip data of different time periods, we cannot make the periods for the five cities line up exactly. To be more specific, Austin, Minneapolis, Louisville, Kansas City, and Portland provide trip data for the periods of April 2018 to May 2020, July 2018 to November 2018, August 2018 to December 2019, January 2019 to December 2019, and July 2018 to May 2020 respectively. Besides, Minneapolis and Austin do not provide coordinates or CBG information of the trip OD after December 2018 and February 2019, respectively. As a result, there is no data of common time periods that could be used for analysis. To eliminate the unobserved seasonal effect, we select the same months, July to September, for the five cities as the study period. During the three months, the climate conditions of the five cities were similar and warm, which was suitable for non-motorized travel. For the five cities, these three months are all within the first year of operation. The characteristics of the ESS trip data of the five cities are shown in Table 1.

Table 2 shows the demographic characteristics and attributes of ESS systems of the five cities. Austin and Louisville designated ESS operating areas, which are 168 and 176 km^2, respectively. The other three cities allow e-scooters to be used in the entire city. This information is important when analyzing the effect of the built environment on ESS ridership (Moran et al., 2020). The number of ESS trips and the number of e-scooters put into use in different cities vary greatly. Austin is the first of the five cities that started the ESS program, which was in April 2018. By May 2020, the number of shared e-scooters in Austin had reached 10,000, which was the highest among the five cities. Portland started the ESS program in 2018, and by May 2019, the number of shared e-scooters had reached 2700. The numbers of e-scooters in Louisville and Kansas City were similar, around 1000. Minneapolis had the lowest number of e-scooters, about 400 by June 2019. We use the number of trips per vehicle per day (TDS) as an indicator to evaluate system performance. The TDS of Austin, which had the most e-scooters, was the lowest. The two cities with the lowest number of e-scooters, Minneapolis and Kansas City, had the highest TDS.

Table 1
Characteristics of the ESS trip data available.

Region	Time period	Number of trips
Austin	From April 2018 to May 2020	9,600,000
Minneapolis	From July 2018 to November 2018, and from May to November 2019	1,921,944
Louisville	From August 2018 to December 2019	505,994
Kansas City	From June 2019 to May 2020	371,000
Portland	July to November 2018, March 2019 to May 2020	1,921,944

Table 2
Demographic and ESS system characteristics of various cities.

	Austin	Minneapolis	Louisville	Kansas City	Portland
Land area (km^2)	845	148	1030	826	375
E-scooter service area (km^2)	168	148	176	826	375
Population (thousand, 2019)	978	429	272	248	654
E-scooter number	10,000	400	1050	1000	2700
Population density (people/ km^2)	1157	2899	264	300	1744
E-scooter density (vehicle/km^2)	73	3	6	1	7
TDS (trip/day/ vehicle)	0.749	2.713	1.281	2.731	2.010
Population/ vehicle	96	1613	588	486	239
Census block group	492	340	410	252	487

The data cleaning process includes two steps. First, we deleted the trips of which the distance is lower than 100 m or longer than 10 km, or the travel time is lower than 60 s or longer than 2 h (Shen et al., 2018). Secondly, we calculated the travel speed by dividing trip distance by trip time and deleted the trips of which the speed is lower than 3.5 km/h or higher than 32 km/h. After the data cleaning process, 1,656,570 records remained for analysis. The origins of the trips are aggregated by CBG using ArcGIS 10.5 for further spatial analysis.

3.2. Explanatory variables

The explanatory variables used in this paper come from the smart location database (SLD) (Ramsey and Bell, 2014) and the open data websites of the five cities. The explanatory variables mainly include demographic characteristics, built environment factors, and regional variables. The demographic characteristics mainly include population density, employment density, median age, median household income, and percentage of no vehicle households of each CBG in the studied area (Census Bureau, 2020). The built environment-related variables, including road design, land diversification, destination accessibility, and density, are selected based on the study of Ewing and Cervero (2010). Regional variables are indicators reflecting the differences of cities, which only includes one variable, population density. The descriptive statistics of variables are shown in Table 3.

Previous studies of ESS found that the built environment factors have a significant influence on ESS trips (Bai and Jiao, 2020; Caspi et al., 2020). This study uses density and diversity-related variables. Density variables include household density, population density, employment density, road density, and intersection density. The population density variables and household density variables in the CBG unit come from the Census Bureau. The employment density is obtained by dividing the number of employments by the area of the CBG based on the census-level employment opportunity data from the longitudinal employer household dynamics (LEHD) program (LEHD, 2019). We obtained the densities of activities, roads, and intersections from the SLD. To measure the level of mixed land use, we use ArcGIS 10.5 to calculate the entropy that represents the level of mixed land use. The equation is as follows:

$$Entropy = \sum_{j \in J} P_j * ln(P_j) \Big/ (lnJ)$$

where j represents the land use index. J is the number of land use types (it equals 5 in this study, and the land use types concerned include office, service, industry, entertainment, and retail). P_j is the percentage of land use of type j. The entropy value of land use ranges from 0 to 1 with 0 indicating single land use type and 1 indicating that the percentages of all land use types are equal.

We consider the number of restaurants as an important factor affecting e-scooter ridership, which is identified by previous studies (Christoforou et al., 2021; Laa and Leth, 2020). Limited parking spaces and traffic congestion in the central business district (CBD) could make people more likely to choose e-scooters for travel. Bai and Jiao (2020) found that university campus was a place where e-scooters are frequently used. Thus, the existence of a university is considered as a potential influencing variable. The universities we choose include University of Texas at Austin, the University of Minnesota at Minneapolis, the University of Portland, the University of Missouri, Rockhurst University, and the University of Louisville. The location of bus stops comes from the open data of each city. Bus stop density in each CBG is calculated using the spatial link function of ArcGIS. This study includes the proportion of households in the CBG that have zero cars and the proportion of people who choose public transportation for commuting. The usage of ESS and the proportion of people choosing public transportation for commuting are assumed to be positively related because ESS can be used as a transfer mode to public transportation. The variable of the number of households with no vehicle may also be positively correlated with ESS ridership.

Table 3
Descriptive statistics of data used in this study.

Variable	Description	Min	Max	Mean	S.D.
E-scooter variables					
Ridership per unit area	Number of e-scooter trips per square km	0	17,690	3429.870	3306.119
Demographic variables at the CBG level					
Household size	Average household size	0	7	2.041	0.778
Median income	Natural log of median household income	9.298	12.430	10.894	0.655
No Vehicle	Percentage of no vehicle households	0	0.782	0.456	0.565
Median age	Median age of households	14.600	63.600	33.637	7.838
Proportion of public transit riders	% of workers who commute by public transit	0	1	0.118	0.119
Built environment variables at the CBG level					
Household density	Household units per square km	0	19,272.000	1894.705	1900.563
Population density	Population per square km	17.530	56,382.080	3086.431	3143.073
Employment density	Employment per square km	1.008	87,510.460	2184.495	3965.305
Distance to center	Distance to the city center (km)	0	19.542	4.600	2.887
Mixed land use	Entropy that represents mixed land use	0	0.992	0.590	0.274
Intersection density	Intersections per square km	0	813.161	108.540	96.647
Road density	Road length per square km	0	55.48	20.986	9.616
Bicycle density	Bicycle trail length per square km	0	19.857	1.206	2.136
Restaurant density	Restaurants per square km	0	439.285	13.258	24.006
University	Number of universities	0	1	0.014	0.120
Bus stop density	Bus stops per square km	0	75	11.500	3.200
Regional variables					
Population density	Population density within the region	582	2899	1459.573	892.330

3.3. Multilevel mixed-effects negative binomial regression

Since the response variable is ridership per unit area, which could be regarded as a count variable, Poisson regression and negative binomial regression are considered as potential models to analyze the data. The distribution of the ridership per unit area is shown in Fig. 1. From the analysis, we find that the mean (2125) of the ridership per unit area is much smaller than its variance (61,996,050), which indicates an over-dispersion problem. As a result, the negative binomial regression is

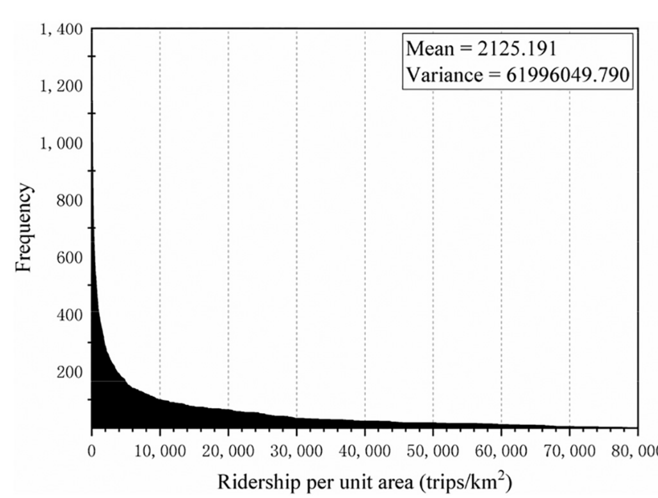

Fig. 1. Distribution of ridership per unit area.

appropriate (Böcker et al., 2020; Wang and Akar, 2019; Younes et al., 2020).

However, the single-level negative binomial regression is not appropriate because the data used in this study has a nesting structure. The CBGs are nested within the cities. Ewing et al. (2015) showed that the multilevel model, also called a hierarchical linear model, is the best way to deal with the data with a nesting structure because it considers the correlation between observations within the cluster, which is the city in our case. Using a single-level model to analyze this type of data would lead to biased parameter estimation (Guo et al., 2021; Raudenbush and Bryk, 2002; Yang et al., 2021). The multilevel modeling approach is used to account for the unobserved correlation between observations within a city due to the shared urban environment. As a result, the multilevel negative binomial regression is used in this study.

$$y_{ik} = \frac{count_{ik}}{area_{ik}},$$

where y_{ik} represents the density of e-scooter trips in the ith CBG in city k, and $count_{ik}$ represents the number of e-scooter trips in the ith CBG in city k. $area_{ik}$ represents the area of the ith CBG in city k.

The model of this study can be written as.

$y_{ik} = \exp(\beta_0 + \beta_m x_{ik} + \beta_n x_k + \upsilon_{ik} + \nu_k + e_{ik})$, where β_0 is the intercept for all CBGs, $\beta_0 + \beta_m x_{ik} + \beta_n x_k$ represents the fixed part of the model, and $\upsilon_{ik} + \nu_k + e_{ik}$ represents the random part of the model. The fixed part of the model represents the overall relationship between e-scooter usage and predicting variables of each CBG. The random part specifies how the region differs from the overall relationship.

In the fixed part, x_{ik} represents a set of predicting variables (i.e., demographic, density, design variables) of CBG i in city k, β_m represents the coefficients of these predicting variables. x_k and β_n represent the city-level variables and their corresponding coefficients in city k. In the random part, υ_{ik} and ν_k represent the random effect at the CBG level and city level, respectively. Maximum likelihood estimation is used to estimate the parameters of the multilevel model.

4. Result

4.1. Data analysis

4.1.1. Temporal distribution of E-scooter trips

Figs. 2 and 3 present the temporal distribution of e-scooter trips by hour during weekdays and weekends, respectively. The temporal variation pattern of ridership of Kansas City is very different from that of other cities. As can be seen, most of the trips in Kansas City happen during the night with the peak hours being 4:00 to 5:00 am, which seems abnormal. As a result, we moved the ridership curve of Kansas City to the right for 8 h, and the adjusted temporal variation pattern of ridership is similar to those of the other cities. The original and adjusted curves of Kansas City on weekday and weekend are also shown in Fig. 2 and Fig. 3, respectively.

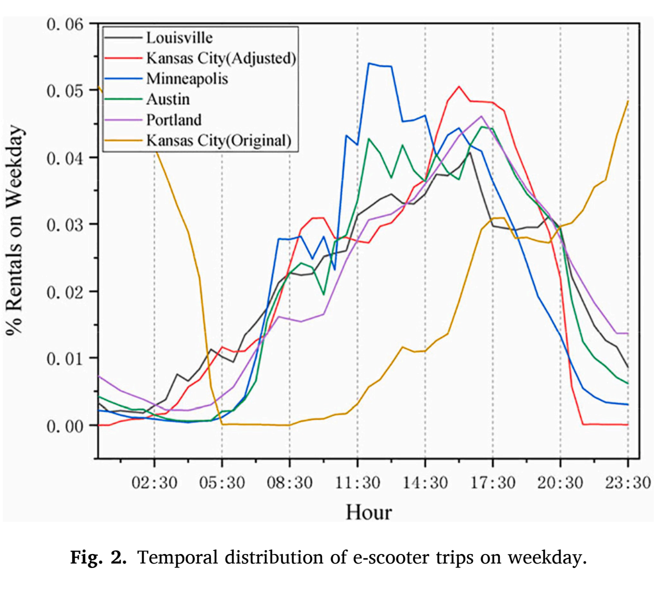

Fig. 2. Temporal distribution of e-scooter trips on weekday.

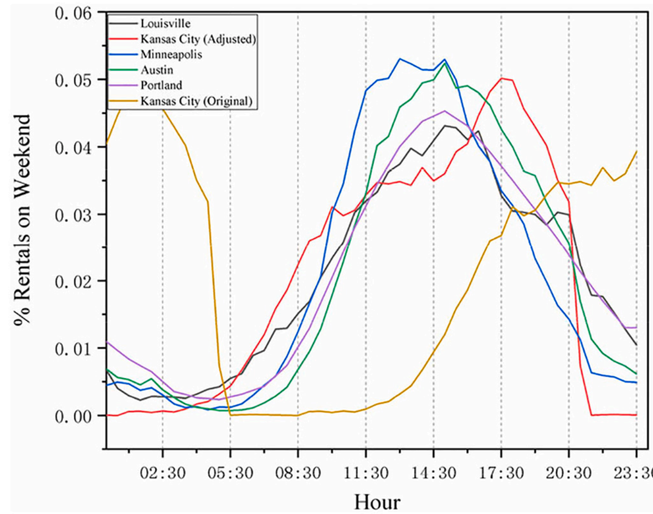

Fig. 3. Temporal distribution of e-scooter trips on weekend.

As shown in Fig. 2, the temporal distribution of trips among various cities is roughly the same as a small difference during the weekday. The peak hours for e-scooter usage are between 11:30 and 17:30. In Minneapolis, the number of trips reaches its peak at around 12 o'clock. This condition could be because a large number of users use e-scooters to eat out during this period. In Portland, the usage reaches the highest at around 18 o'clock in the evening, matching the evening peak hours. This condition can be because people choose e-scooters for going back home or going to places for entertainment during this time. The temporal distributions of ridership of Louisville and Austin are similar, and the e-scooter usage is high between 12 and 17 o'clock.

Fig. 3 shows the temporal distribution of e-scooter usage on weekends. The temporal variation pattern of the ridership of the five cities is similar though the peak hours of the five cities are somehow different. The highest ridership for Minneapolis happens at around noon. But for Kansas City, it is around 16:30. Despite the difference, the peak hours for the five cities are usually between 11:30 and 17:30.

To sum up, the peak hours and non-peak hours for the ESS trips are different from those of other typical transportation modes, such as automobile and subway. The peak hours for ESS trips are usually between 11:30 and 17:30. It should be noted that we are not totally sure that shifting the curve of Kansa City to the right for eight hours is the correct solution. The data provider of the Kansas City could not verify whether the abnormal temporal variation of ridership was due to an error in the data or the actual case. If the data was correct, it could be because people going between bars and clubs at night usually use shared e-scooters.

4.1.2. Spatial distribution of ESS trips

Fig. 4 shows the spatial distribution of ESS trips in the five cities. The spatial distributions of the five cities are different. For cities with a high number of e-scooters, such as Austin (with 10,000 e-scooters), the trips mainly start in the city center and surrounding areas. For cities with a medium number of e-scooters, such as Louisville (with 1000 e-scooters), trips have a dispersed spatial distribution. Minneapolis (with 400 e-scooters) has a more dispersed distribution of trips than cities with a medium number of e-scooters. Although the distribution of trips of each city is different, one pattern is the same: the number of trips originating

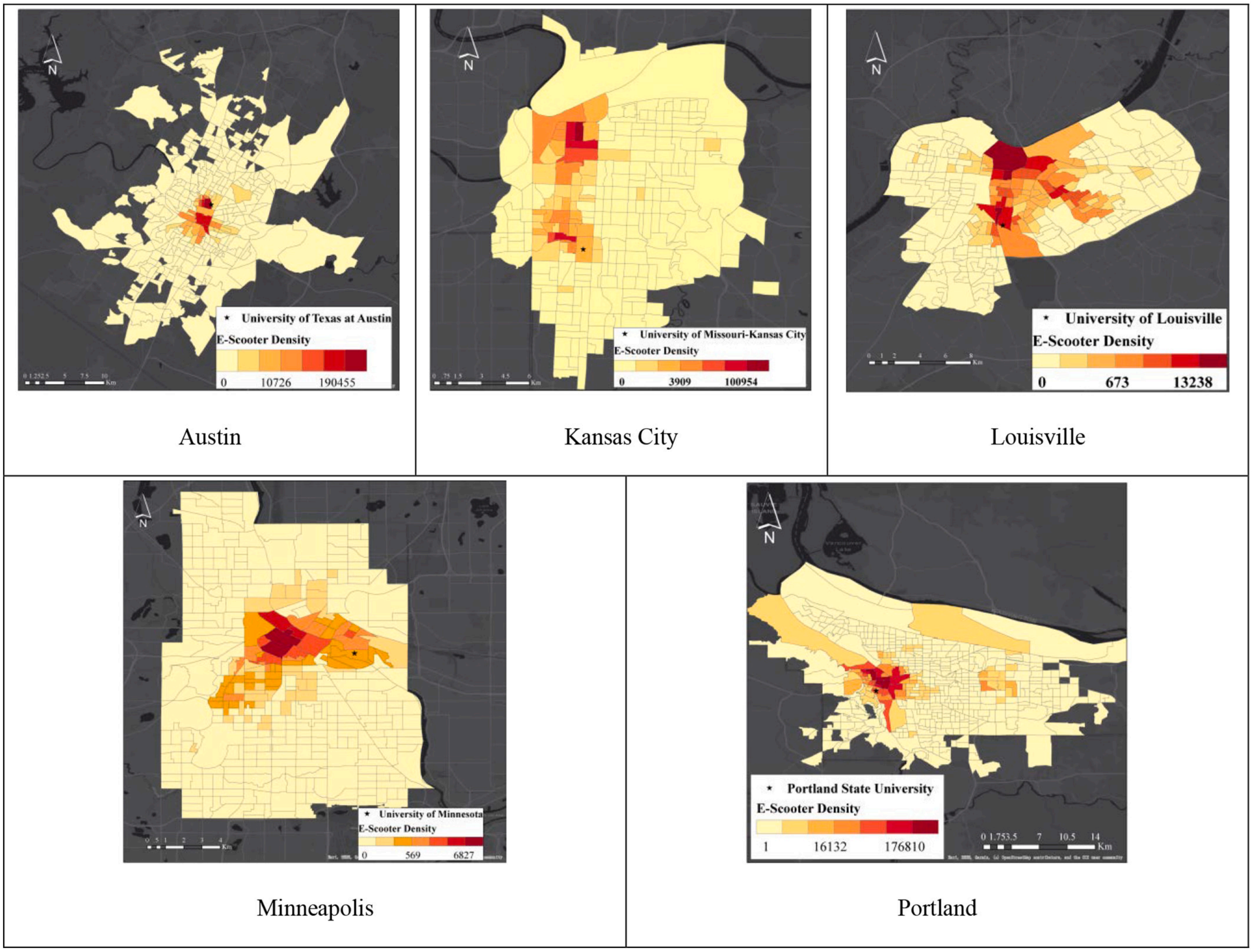

Fig. 4. Spatial distribution of ESS trips.

from the city center is the highest. The operation areas of the five cities, Austin, Minneapolis, Kansas City, Louisville, and Portland all contain universities, and many ESS companies have launched pilot projects in universities to facilitate students' use (Lime, 2019). The high usage around universities shows that ESS is extremely popular among university students.

4.1.3. Distribution of ESS trip duration and distance

Fig. 5 compares the distribution of ESS trip duration of the five cities. No significant difference is found in the distribution of ESS trip duration among the five cities. Most of the users ride e-scooters for 3 min to 8 min. A curve representing the cumulative probability distribution of ESS trip duration of all cities is drawn in Fig. 5. From that curve, the duration of 90% of ESS trips is within 30 min, and that of 80% of the trips is within 20 min.

Fig. 6 visualizes the distribution of ESS trip distances of the five cities. The trip distance of different cities follows a similar distribution, with the peak being around 0.5 km. A curve representing the cumulative probability distribution of the ESS trip distance of all cities is drawn. From that curve, 90% of ESS trips are less than 3 km, and 80% of ESS trips are within 2 km. Previous studies found that the average trip distance of docked bike sharing was 2 km (Divvy, 2015; Yang et al., 2020). This shows that the average trip distance of ESS is shorter (1.7 km) than that of bike sharing.

Fig. 7 shows the speed distribution of ESS in different cities. As can be seen, the average speed of different cities is slightly different, which ranges from 7.2 km/h to 12.6 km/h. A curve representing the cumulative probability distribution of ESS speed of each city is drawn. From that curve, the speed of 90% of ESS trips is less than 18 km/h, and that of 80% of ESS trips are less than 14.4 km/h.

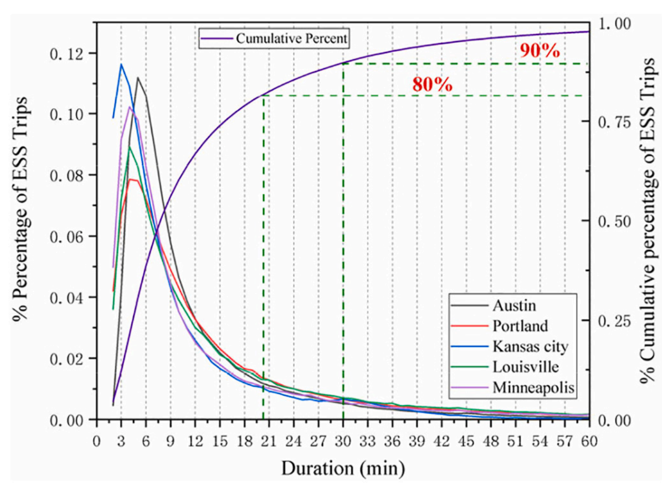

Fig. 5. Distribution of ESS trip duration in five cities.

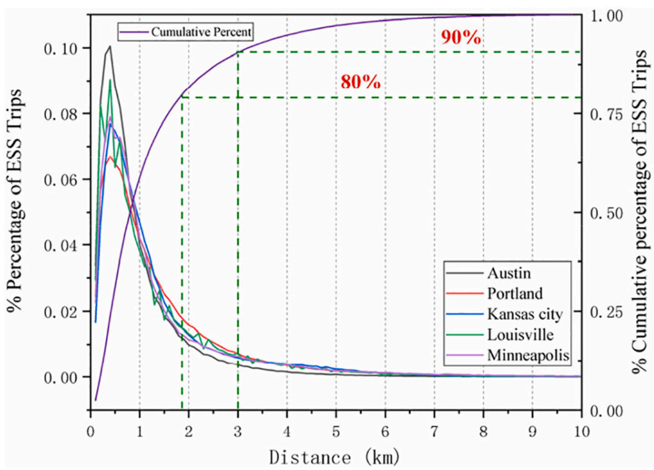

Fig. 6. Distribution of ESS trip distance in five cities.

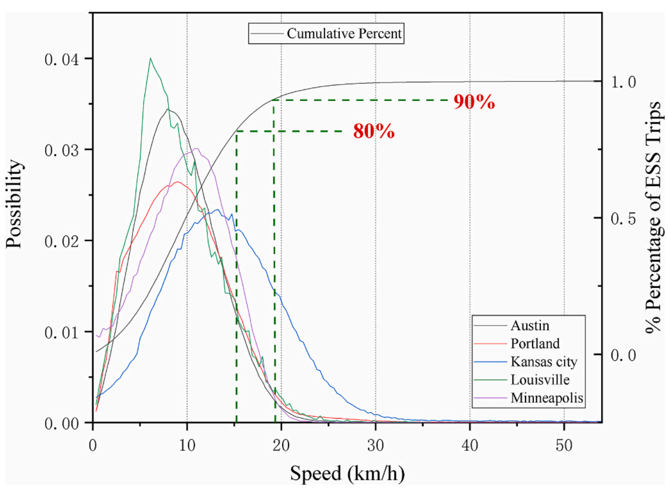

Fig. 7. Distribution of ESS speed in five cities.

4.2. Model results

In this part, we discuss the influence of the built environment on ESS ridership by modeling and analyzing the ridership data of weekends and workdays separately. We first use the correlation coefficient to check the possible multicollinearity problem in the model and use the rule of thumb that the correlation coefficient should not exceed 0.6 to eliminate some variables. The correlation coefficient between household density and population density is 0.9. We delete the variable of household density. Besides, we calculated the elasticity of the explanatory variables in the weekday and weekend models. Elasticity is the percentage change of a variable resulted from a percentage change in another variable (Ma et al., 2017; Wang and Akar, 2019).

4.2.1. Demographic variables

As shown in Table 4, the e-scooter ridership is positively correlated with the median household income of a CBG. This finding reinforces previous findings in the existing literature that the ridership of e-scooters is higher in areas with higher income levels (Christoforou et al., 2021). This probably because the cost of e-scooter is higher than the cost of public transportation (Washington Post, 2019).

Previous studies showed that in Minneapolis, young people are likely to use e-scooters, and this finding is verified in our study (Bai and Jiao, 2020; Laa and Leth, 2020). Our research results show that the median age of people in the CBG has a negative correlation with e-scooter usage. This finding is consistent with our expectation that as a new type of shared micromobility, e-scooters are easily accepted and used by young people who are interested in new technology (Laa and Leth, 2020; Lime, 2020). The median age is more important than other socioeconomic variables on weekdays based on the result of elasticity analysis.

4.2.2. Car ownership and commute characteristics

From our results, the proportion of households without a car in the household is negatively correlated with the ridership, which is contrary to our assumption. This condition is possibly because the number of cars owned by a family is positively related to the family income. The model results of this study show that family income is positively related to high electric scooter travel. Thus, the coefficient for the variable proportion of households without a car is negative.

The temporal distribution of ridership shows that the ESS ridership is

Table 4
Multilevel model results.

Variable type	Variables	Coef.	Std. err.	Elasticity (%)	*p* value	Coef.	Std. err.	Elasticity (%)	p value
		Weekday				Weekend			
	Intercept	4.555	0.769		0.000	2.884	0.761		0.000
Demographic	Median income	0.025	0.063	0.267	0.696	0.128	0.061	1.391	0.063
	No vehicles	−1.084	0.383	−0.544	0.002	−1.309	0.375	−0.604	0.000
	Median age	−0.020	0.005	−0.678	0.000	−0.014	0.005	−0.460	0.001
	Proportion of public transit riders	0.930	0.428	0.110	0.030	0.204	0.440	0.024	0.805
Built environment	Population density (*10ˆ3)	0.1.95	0.002	0.601	0.000	0.014	0.002	0.431	0.000
	Employment density (*10ˆ3)	0.044	0.001	0.096	0.000	0.043	0.001	0.093	0.000
	Distance to center (*10ˆ3)	−0.266	0.001	−1.225	0.000	−0.026	0.001	−1.185	0.000
	Bicycle density	0.073	0.023	1.542	0.000	0.086	0.024	1.812	0.000
	Road density	0.066	0.007	0.079	0.000	0.058	0.009	0.070	0.000
	Intersection density	0.002	1.0*10ˆ-5	0.236	0.000	0.002	1.0*10ˆ-5	0.230	0.000
	Land mix use	0.768	0.123	0.453	0.000	0.862	0.128	0.509	0.000
	School university	2.129	0.552	0.034	0.000	1.663	0.538	0.025	0.000
	Restaurant density	0.017	0.005	0.220	0.000	0.018	0.002	0.235	0000
	Bus stop density	0.026	0.004	0.304	0.000	0.100	0.017	1.154	0000
Regional	Population density (*10ˆ3)	0.045	0.006	0.670	0.000	0.032	0.005	0.580	0.000
Variation at different levels									
Var(cons)-Region		1.054	*N* = 5			0.418	N = 5		
Var(cons)-CBG		1.684	*N* = 2021			0.815	N = 2021		
Model evaluation									
Log-likelihood (LL(β))		−12,223.572				−10,348.031			
AIC		24,583.14				20,732.06			
BIC		24,584.14				20,831.25			

not high during the morning peak hours, indicating it is not one of the major commuting transportation modes. However, the variable the percentage of residents who use public transit for commuting is significantly positively related to ESS ridership, which reveals that ESS could possibly serve as a feeder mode to public transit and that public transit users may be more likely to use ESS than non-users.

4.2.3. Built environment variables

The significant variables include both transit supply features and land use variables. The density variables appear to be important determinants of e-scooter trips because both population and employment density variables are positive and significant in weekday and weekend models. This result is consistent with that of previous studies (Bai and Jiao, 2020; Caspi et al., 2020; Hosseinzadeh et al., 2021a). Similarly, the population density of the city is also significantly positively related to ESS ridership.

Consistent with the finding on the spatial distribution of ESS trips, the closer the CBG to the city center, the higher ESS ridership there is. The main reason could be that there are more activities in the city center with limited parking spaces, and thus shared e-scooter could replace private vehicles to serve as a transportation mode to meet these derived demands.

The usage of e-scooters is promoted if a university is found in the CBG, which is consistent with the result of a previous study (Hosseinzadeh et al., 2021b). The reason why the ridership is high in the university may be that in addition to the high density of land use and students, ESS is the ideal transportation tool for the common short-distance trips on campus such as going to classes and going to the cafeteria for food. Many e-scooter operators have also signed partnerships with universities to allow the vehicles to be placed on campus. Lime, for example, has partnered with the University of Minnesota at Minneapolis and University of Texas at Austin (Lime, 2019). A positive correlation is found between the number of restaurants and e-scooter ridership, which indicates that people usually use ESS to go to restaurants.

Regarding land use diversity, the variable entropy is positively correlated with the number of e-scooter trips. This could be explained by the findings of previous studies that high land use diversity shortens people's travel distance, reduces people's use of cars to travel, and promotes non-motorized transportation modes, especially the electric alternatives (Duran-Rodas et al., 2019; Hosford and Winters, 2018).

Regarding design-related variables, a positive correlation is found between intersection density and e-scooter ridership in the CBG. This is consistent with the findings of Caspi et al. (2020). This could probably be because those e-scooter riders have more alternative routes to reach the destination in areas with high intersection density and thus have higher destination accessibility (Chen and Ye, 2021; Yang et al., 2017). Based on the elasticity analysis result of this variable, the ridership increases by 0.24% per unit area when the intersection density increases by 1%. In terms of bicycle facility, the density of bicycle trail density is positively associated with e-scooter ridership, indicating that increasing the density of bicycle trail can probably promote the use of e-scooters. This condition is probably because e-scooters can be ridden in the bicycle trail with a high comfort and safety level. The elasticity analysis shows that a 1% increase in the density of bicycle trails leads to a 1.18% increase in e-scooter ridership.

The model results indicate that the bus stop density is positively related to e-scooter ridership. This result is consistent with that of previous studies (Caspi et al., 2020). However, it should be noted that areas with high bus stop density are mainly located in the city center with more activities. As a result, whether the high ESS ridership is due to the high bus stop density or because the area is in the city center is still not clear, which requires further investigation.

5. Conclusion

5.1. Summary

This study uses ESS trip data of multiple cities to explore the spatial and temporal distributions of ESS trips and to study the factors affecting the e-scooter trips. A multilevel model is used to analyze the data to obtain a general and robust conclusion. The built environment and socioeconomic variables are considered as potential influencing factors. The results of the study can help operators determine areas with high ridership and how the e-scooter ridership changes when the built environment changes.

Analysis results show that the temporal distributions of e-scooter ridership of the five cities are similar for both weekdays and weekends. The hourly ridership increases in the morning and reaches the peak of the day from 11:30 to 17:30 and declines after that time period. The daily ridership on weekdays is higher than that on weekends. Regarding the spatial distribution of e-scooter trips, e-scooter ridership is high in areas with universities and CBD areas.

A multilevel negative binomial regression model is constructed to analyze the factors affecting the e-scooter trips on weekdays and weekends. Regarding demographic variables, the proportion of households with no cars and the median age of all the people in the CBG are negatively related to ESS ridership on both weekdays and weekends. The proportion of residents who commute by public transportation and the median income of people in the CBG are positively related to the ESS ridership in the weekday and weekend model, respectively. It indicates that ESS may be more popular among young people, people with higher income, and people who use public transportation for commuting. Regarding the built environment, population density, employment density, intersection density, land use diversity, bus stop density, and the number of universities of the CBG are positively related to the ESS ridership while the distance between the CBG and city center is negatively related to the ESS ridership. It shows that ESS ridership is high at places with more activities and that ESS could possibly serve as a feeder mode to public transportation.

5.2. Limitations and future research

This study has several limitations. First, due to the limitation of the data, the data analyzed by this study are not from the same periods. They come from the same months but different years. This could eliminate the seasonal effect, though the other unobserved temporal effects may still exist. Besides, the data are all from the first year of operation, which also indicates using this set of data might not be a significant limitation. The similar temporal variations of the ridership within a day of the five cities also imply the unobserved temporal effects might be insignificant. But still, it would be better if the data of the same months of the same year could be obtained.

Secondly, the effects of peak hours and weather on ESS ridership are not explored by this study because incorporating the temporal dimension in the multilevel model would result in a much more complex model with lower interpretability.

Thirdly, the spatial dependence of CBG within a city was not fully accounted for in this study. Although this type of dependence is usually not accounted for in multiple-city studies due to the complexity of the model that is needed (Ding and Cao, 2019; Ewing et al., 2015; Sabouri et al., 2020), future research should try to address this issue to obtain more accurate parameter estimation.

Despite these limitations, this study obtains more generalizable and robust results on the spatiotemporal distribution of ESS ridership and the relationship between the built environment and ESS ridership. The results of this study could serve as a reference for government agencies and ESS operators to understand how the built environment influences the ESS ridership, determine high-ridership area, and to estimate the change of ridership when the built environment changes.

Author contributions

The authors confirm contribution to the paper as follows: study conception and design: H. Yang, J. Huo, C. Li, R. Zheng, L. Yang; data collection: J. Huo, C. Li; analysis and interpretation of results: H. Yang, J. Huo, C. Li; draft manuscript preparation: H. Yang, J. Huo, C. Li, R. Zheng, Y. Wen. All authors reviewed the results and approved the final version of the manuscript.

Declaration of Competing Interest

None.

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