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Exploring spatial heterogeneity of e-scooter's relationship with ridesourcing using explainable machine learning

Junfeng Jiao, Yiming Xu *, Yang Li

School of Architecture, The University of Texas at Austin, 310 Inner Campus Drive, B7500, Austin, 78712, TX, United States

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ABSTRACT

The expansion of e-scooter sharing system has introduced several novel interactions within the existing transportation system. However, few studies have explored how spatial contexts influence these interactions. To fill this gap, this study explored the spatial heterogeneity in e-scooter's relationship with ridesourcing using data from Chicago, IL. We developed a Light Gradient Boosting Machine (LightGBM) to estimate e-scooter sharing usage using ridesourcing trips along with associated built environment and socio-demographic variables. The model was interpreted using SHapley Additive exPlanations (SHAP). Results indicated that the threshold effects, where the positive relationship between e-scooter sharing and ridesourcing significantly weakened beyond a certain value, were more pronounced in areas with lower population density, fewer jobs, and fewer young, highly educated population. This is primarily attributed to the limited competitiveness of e-scooter sharing in these areas. These findings can assist cities in harmonizing e-scooter sharing and ridesourcing thus promoting sustainable transportation systems.

1. Introduction

E-scooter sharing is an innovative instance of shared micromobility that provides dockless electric scooters for short-term rental. This mode of transportation has increasingly become a crucial element of urban transportation systems in North America and has continued to recover from the pandemic era. In 2022, riders in the U.S. and Canada took 58.5 million trips on shared e-scooters, indicating a 70% increase from 2020 (NACTO, 2023). Appealing for short-distance trips, e-scooter sharing continuously contributes to replacing car trips by providing a reliable mode of transportation for residents to access various city amenities, therefore reducing urban traffic and cutting down on greenhouse gas emissions. However, some issues, such as safety concerns, curb space violations, and unbalanced spatiotemporal demand, hinder the growth of e-scooter sharing systems (NACTO, 2023; Merlin et al., 2021; Xu et al., 2022, 2023; Guo and Zhang, 2021; Xu et al., 2024). Given the mixed impact of e-scooter sharing on urban transportation, marked by both benefits and challenges, significant efforts are needed to understand its usage patterns to enhance urban mobility.

The expansion of e-scooter sharing services has led to several novel interactions within the existing transportation system (Guo and Zhang, 2021; Yang et al., 2021; Guo et al., 2023). Due to its flexibility and affordability, e-scooter is particularly attractive to leisure trips and short-distance trips in urban areas (Xu et al., 2022; Shah et al., 2023; Bai et al., 2021; Cao et al., 2021). The ridesourcing services, such as Uber and Lyft, also offer competitive options for these trips within urban areas (Xu et al., 2021; Rayle et al., 2016). Since these two travel modes share advantages such as convenience and affordability, they are likely to either compete or complement each other (Liao, 2021; Becker et al., 2020; McKenzie, 2020). Considering the expenses involved in maintaining and

* Corresponding author.
E-mail address: yiming.xu@utexas.edu (Y. Xu).

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operating systems for both modes, excessive competition could lead to higher public utility costs and an increased burden on social operations. Therefore, an in-depth understanding of their interaction is necessary for cities to guide a beneficial relationship between these two travel modes, thereby promoting a sustainable transportation system.

However, few existing studies have illuminated the connection between shared e-scooter and ridesourcing, especially the variation of their relationship across a geographical area (i.e., spatial heterogeneity). Despite some recent efforts to explore the impact of e-scooter sharing on auto mode substitution (Guo and Zhang, 2021; Lee et al., 2021b), most existing studies on e-scooter's interactions with other travel modes focus on its relationship with bike sharing and transit (Guo et al., 2023; Yang et al., 2021; Reck et al., 2021; Zhu et al., 2020). In these studies, the e-scooter's relationship with other travel modes is usually identified as a binary or categorical variable (e.g., competitive/complementary). This variable is then used as the dependent variable in the modeling process to examine its association with the built environment and social demographic variables. While the relationship is much more complex to be represented by binary or categorical variables, some insights may be overlooked in these studies. To fill this research gap, this study directly includes the demand of another travel mode (i.e., ridesourcing) as an independent variable to model their relationship. Then we examine the interaction effect of ridesourcing and a specific spatial variable on e-scooter sharing to understand how this variable influences e-scooter's relationship with ridesourcing.

In addition, the associations between e-scooter sharing and built environment, as well as social demographic variables, are usually non-linear. They are typically marked by threshold effects and dynamic marginal values (Yang et al., 2022; Jin et al., 2023). For example, e-scooters are attractive to young people due to their fun factors (Bai and Jiao, 2020; Jiao and Bai, 2020), leading to an increase in e-scooter sharing usage as the percentage of young population increases. This increase may be significant when the percentage of young population is below a threshold and then becomes insignificant after it exceeds this threshold. Such non-linear effects cannot be well captured by linear models (e.g., ordinary least squares regression and logit model) when multicolinearities and complex relationships exist among the independent variables. In contrast, machine learning models with flexible structures, like random forests (RF) and gradient-boosted decision trees (GBDT), are well-suited to modeling these non-linear effects (Yang et al., 2022; Jin et al., 2023; Xu et al., 2021). The rapidly evolving model interpretation methods provide researchers with powerful tools to access nonlinearities in these black-box machine learning models (Guo et al., 2023; Xu et al., 2021). These model interpretation methods, such as feature importance, shapley additive explanations (SHAP), and partial dependence plots (PDP), have been successfully applied to interpret RF and GBDT models in existing travel behavior studies (Cao and Tao, 2023; Tao et al., 2023; Xu et al., 2021; Guo et al., 2023; Yang et al., 2022; Jin et al., 2023; Zhang et al., 2024). This study incorporates these explainable machine learning methods to explore the spatial heterogeneity of e-scooter's relationship with ridesourcing.

In light of the above, we apply a Light Gradient Boosting Machine (LightGBM) to explore the spatial heterogeneity in the relationship between shared e-scooter's usage and ridesourcing usage, and then interpret the model using feature importance and SHAP. Specifically, we adopt a LightGBM to evaluate the daily e-scooter sharing usage based on daily ridesourcing usage, built environment factors, and socio-demographic factors. After fine-tuning the model, we calculate the feature importance and SHAP value for each feature. Then we analyze the interactive effects of ridesourcing together with key built environment and socio-demographic variables on e-scooter sharing usage to understand e-scooter's relationship with ridesourcing in different spatial contexts. This study contributes to existing knowledge on the spatial heterogeneity of the relationship between e-scooter sharing and ridesourcing, providing guidance to cities in harmonizing these two travel modes and promoting sustainable transportation systems.

Section 2 reviews the literature on factors influencing e-scooter sharing and its interaction with other travel modes. In Section 3, we describe the details of the modeling and interpretation process. Section 4 introduces the data for a case study in Chicago, IL. Section 5 presents the detailed results of the case study. Section 6 discusses the insights based on the results. In Section 7, we wrap up this paper by summarizing results and insights and indicating the strengths and limitations of the study.

2. Literature review

2.1. Factors associated with E-scooter sharing

Researchers have delved into various factors to comprehend their impact on the use of e-scooter sharing services. These factors fall into three primary categories: socio-demographics, built environment, and land use.

The demographics, such as age, gender, income, education level, race, marriage status, and resident status, significantly influence e-scooter sharing usage. Studies indicate a higher propensity for e-scooter sharing usage among young individuals, males, those with higher income, high-educated, and single individuals (Lee et al., 2021a; Cao et al., 2021; Mitra and Hess, 2021; Christoforou et al., 2021; Laa and Leth, 2020; Sanders et al., 2020). However, some recent studies also found that highly educated individuals were less willing to use shared e-scooters due to health consciousness (Blazanin et al., 2022; Araghi et al., 2022). Furthermore, certain zonal socio-demographic characteristics, such as population density, employment rates, the proportion of young people, and the proportion of people with advanced degrees, also positively correlate with e-scooter sharing usage (Merlin et al., 2021; Bai and Jiao, 2020; Caspi et al., 2020).

The primary built environment factor related to e-scooter sharing is transportation supply, with a particular emphasis on the quality of the riding environment and street safety (Mitra and Hess, 2021; Sanders et al., 2020; Hosseinzadeh et al., 2021). Areas with superior riding conditions, featured with higher walkability index, bikeability index, and better cycling facilities, usually experience a higher amount of e-scooter sharing trips (Hosseinzadeh et al., 2021; Caspi et al., 2020; Jiao and Xu, 2024). Additionally, higher density of transit stations is associated with increased shared e-scooter usage (Bai and Jiao, 2020; Merlin et al., 2021). The distance that users need to walk to access or leave e-scooters also influences their willingness to use these services (Cao et al., 2021).

Land use factors also play a crucial role in the usage patterns of e-scooter sharing. Greater land use diversity and higher commercial area proportion are positively associated with the demand for shared scooters (Hosseinzadeh et al., 2021; Bai and Jiao, 2020; Merlin et al., 2021).

2.2. E-scooter's interaction with other modes

Previous research has investigated how e-scooters interact with various travel modes, including bike sharing, public transit, walking, and auto mode.

As key components of shared micromobility, e-scooter sharing and bike sharing share advantages such as flexibility and convenience, both of which are ideal for short-distance trips (McKenzie, 2019, 2020; Xu et al., 2022; Sanders et al., 2020). These similarities lead to overlapping usage patterns, including trip distance, travel time, and trip purpose (McKenzie, 2019, 2020; Su et al., 2023; Zhu et al., 2020; Reck et al., 2021; Reck and Axhausen, 2021; Younes et al., 2020). Therefore, competition and complementation may exist between these two shared micromobility modes. Studies suggested that e-scooter sharing, as a new player in the shared micromobility market, can substitute bike sharing trips thus reducing bike sharing usage (Sanders et al., 2020; Lee et al., 2021a; Yang et al., 2021). For example, Yang et al. (2021) indicated that e-scooter sharing reduced the short-term, medium-term, and long-term bike sharing trips by 7.5%, 9.6%, and 20.5%, respectively, contributing to a 10.2% decline of overall bike sharing trips in Chicago, IL. On the contrary, e-scooter sharing and bike sharing can complement each other due to behavioral spillover effects and psycho-social attitude factors (Blazanin et al., 2022). Efforts to promote e-scooter sharing can have complementary spillover effects on promoting bike sharing (Blazanin et al., 2022). In addition, the connection between e-scooter sharing and bike sharing can be mixed. Younes et al. (2020) found that in Washington, D.C., e-scooter sharing competed with non-member station-based bike sharing, while it had a complementary relationship with member station-based bike sharing.

E-scooter sharing is considered to have the potential to address the "first-mile/last-mile" problem (Xu et al., 2022; Merlin et al., 2021; Yan et al., 2023). By the "e-scooter + transit" (scoot-N-ride) use form, e-scooter sharing has the potential to enhance public transit, thus complementary to public transit (Yan et al., 2023; Ziedan et al., 2021). On the contrary, e-scooter sharing can also replace transit trips in certain contexts (Guo et al., 2023; Reck et al., 2021; Ziedan et al., 2021; Luo et al., 2021). For example, studies in Stockholm and Helsinki suggested that the competition between e-scooter sharing and transit was more excessive in areas with better transit accessibility (Guo et al., 2023).

The expansion of e-scooter sharing also influenced walking and auto-mode trips. Studies suggested that e-scooter sharing was replacing walking trips for all trip purposes, particularly in the heat (Sanders et al., 2020). E-scooter sharing also competed with auto-mode trips such as driving, taxi, and ridesourcing, in short distance, lower cost, or social/entertainment trips (Sanders et al., 2020; Guo and Zhang, 2021; Lee et al., 2021b; Yan et al., 2023).

Although e-scooter's interaction with bike sharing, transit, walking, and auto mode has been extensively investigated in the literature, studies on spatial heterogeneity of e-scooter's relationship with ridesourcing are lacking, which motivates this study.

3. Methodology

We use a Light Gradient Boosting Machine (LightGBM) to model the spatial heterogeneity of e-scooter's relationship with ridesourcing, and then use the SHapley Additive exPlanations (SHAP) values to further explain the model. We introduce the details of LightGBM and SHAP in the following sections.

3.1. Light Gradient Boosting Machine

Light Gradient Boosting Machine (LightGBM) is an ensemble tree-based learning method based on the gradient boosting mechanism (Ke et al., 2017). LightGBM uses Gradient-based One-Side Sampling (GOSS) and Exclusive Feature Bundling (EFB) to achieve high training efficiency and better accuracy with low memory usage. The GOSS process randomly excludes data instances with small gradients and keeps all instances with large gradients. The EFB process bundles mutually exclusive features, thus reducing feature dimensionality to improve efficiency while maintaining high accuracy.

As a tree-based gradient boosting framework, LightGBM is efficient in handling large-scale and high-dimensional data. LightGBM is also robust enough as it is insensitive to skewed data distributions, missing values, and outliers. Additionally, the flexible modeling structure of LightGBM enables it to effectively capture complex nonlinear relationships between independent and dependent variables. This is particularly advantageous for our study, as the relationships between e-scooter sharing and factors such as the built environment and social demographics are typically non-linear.

LightGBM has several hyperparameters for fine-tuning to reduce overfitting and maximize model performance. These hyperparameters include boosting-related parameters, such as the number of boosted trees and the boosting learning rate, and tree-related parameters, such as maximum tree depth and maximum tree leaves for base learners. The best combination of the values of these hyperparameters can be approximated using the grid search method.

3.2. Shapley additive explanations

SHapley Additive exPlanations (SHAP) is a model interpretation method to interpret individual estimation by calculating each feature's contribution to estimation (Lundberg and Lee, 2017). In SHAP, the feature values of an instance are considered as coalitional players. It uses Shapley values for fairly allocating each feature's contribution towards the final estimation (Molnar, 2020). The Shapley values are computed by:

$$\phi_j(v) = \sum_{S \subseteq N \setminus \{j\}} \frac{|S|!(|N| - |S| - 1)!}{|N|!} [v(S \cup \{j\}) - v(S)] \tag{1}$$

Table 1
Model performance.

Model	In-sample		Out-of-sample	
	RMSE	MAE	RMSE	MAE
OLS	60.7793	28.5873	60.8518	28.6334
DT	37.4390	14.7503	42.0619	16.2012
RF	**34.1366**	**13.7782**	41.6640	15.9498
MLP	60.2137	28.2018	60.8591	28.3563
LightGBM	37.6119	14.4191	**40.6485**	**15.4473**

where $\phi_j(v)$ represents the Shapley value for feature j; N denotes the universal feature set; S is a feature subset excluding feature j; $|S|$ is the cardinality in S; $|N|$ is the total number of features; $v(S)$ is the estimation of the model with only the features in set S; $v(S \cup \{j\})$ is the estimation of the model with the features in S and feature j. The summation is taken over all subsets S of the set N that do not include feature j. The fraction $\frac{|S|!(|N|-|S|-1)!}{|N|!}$ acts as a weighting factor for each subset.

We use the SHAP Feature Importance to evaluate the contribution of each feature to the model estimation. The SHAP Feature Importance is calculated by:

$$I_j = \frac{1}{n}\sum_{i=1}^{n} |\phi_j^{(i)}| \tag{2}$$

where I_j is the feature importance for feature j; n is the number of data instances; $\phi_j^{(i)}$ is the Shapley value for feature j in instance i.

We use the SHAP Interaction Values to understand the influence of a spatial variable on the relationship between e-scooter sharing and ridesourcing. Specifically, we compute the SHAP interaction value for the ridesourcing usage grouped by spatial factors and then visualize it in a colored scatter plot.

3.3. Model performance

The LightGBM model was tuned using grid-search for hyperparameters including the number of boosted trees, boosting learning rate, and maximum tree depth. The grid-search used 10-fold cross-validation and $L2$ loss. According to the grid search results, the optimal number of boosted trees, boosting learning rate, and maximum tree depth are 2000, 0.01, and 20, respectively.

We further conducted a comparative analysis of the model fit and predictive performance between the LightGBM model and four benchmark models: Ordinary Least Squares (OLS), Decision Tree (DT), Random Forest (RF), and Multi-Layer Perceptron (MLP). Note that all the benchmark models were fine-tuned using grid-search with 10-fold cross-validation and $L2$ loss. We evaluated model effectiveness using Root Mean Squared Error (RMSE) and Mean Absolute Error (MAE) for both in-sample and out-of-sample data. The two evaluation metrics are calculated by:

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(\hat{y}_i - y_i)^2} \tag{3}$$

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|\hat{y}_i - y_i| \tag{4}$$

where n is the total number of observations, y_i is the ith observed value for the dependent variable, $\hat{y}_i$ is the ith model estimation.

The performance of LightGBM and benchmark models is presented in Table 1. According to the results, the LightGBM model outperformed the other models with the out-of-sample observation (i.e., test data), and it had similar in-sample and out-of-sample performance. This results from LightGBM's robustness to overfitting and its leaf-wise growth which reduces loss more effectively. On the contrary, although the RF model had the best in-sample performance, there were significant overfitting issues in the RF model. Therefore, the LightGBM model is the most appropriate model for further analysis.

4. Data

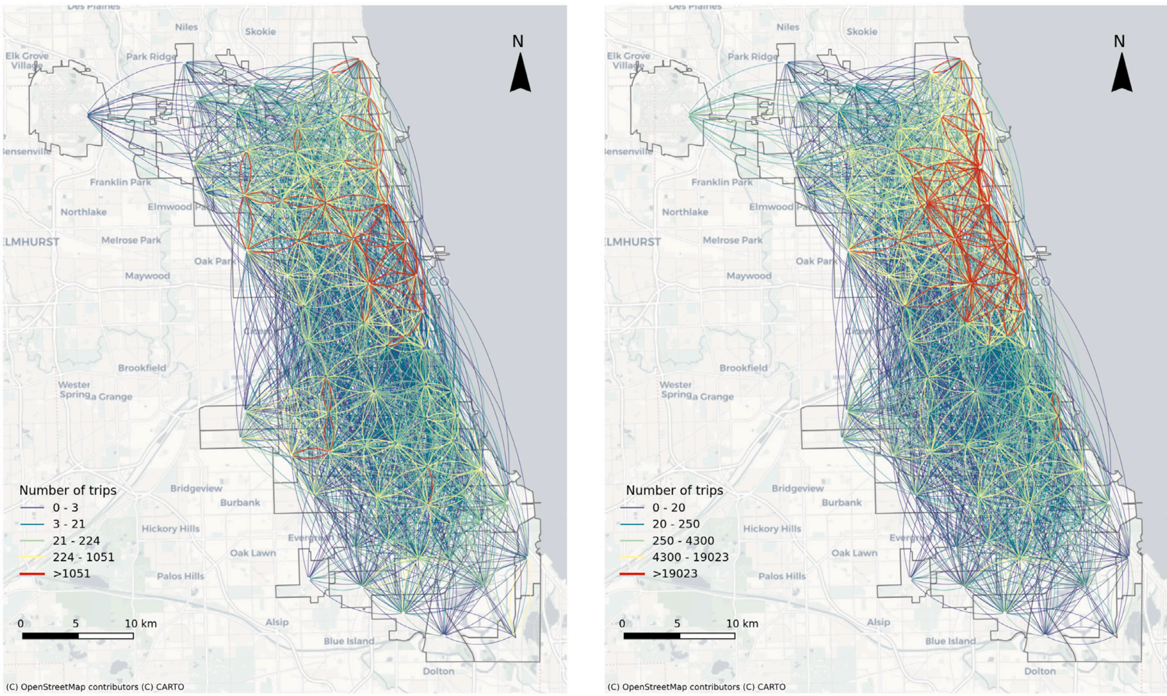
This study employs data from Chicago, IL as a case study. The data includes e-scooter sharing trip data, ridesourcing trip data, socio-demographic data, and built environment data. Table 2 presents a detailed overview of the descriptive statistics for the variables.

The e-scooter sharing and ridesourcing trip data were sourced from the Chicago Data Portal.[1] To ensure privacy, the data provider rounded the time to the nearest quarter-hour and aggregated the location information at the Community Area level. For our analysis, we processed the trips from individual trip records to an aggregated level (i.e., trip count), focusing on origin–destination (O–D) pairs within Community Areas. Temporally, we included e-scooter sharing and ridesourcing trips spanning from May to December

[1] https://data.cityofchicago.org/.

Table 2
Descriptive statistics of variables.

Variable	Unit	Mean	St. dev.	Min.	Max.
E-scooter trip count	–	37	80	5	1168
Ridesourcing trip count	–	500	1001	1	16 218
Socio-demographic variables					
Percentage of female population	–	52.26%	3.46%	45.14%	62.60%
Percentage of population aged 18–35	–	26.53%	7.96%	13.45%	49.16%
Percentage of white population	–	39.87%	28.19%	0.81%	89.50%
Percentage of black population	–	36.53%	38.91%	0.49%	97.36%
Percentage of population with bachelor's degree and above	–	24.67%	17.43%	3.28%	70.89%
Unemployment rate	–	10.88%	6.89%	1.82%	32.97%
Percentage of household with vehicle	–	76.46%	12.77%	51.39%	96.26%
Median household income	US dollar	64 707	29 445	19 605	144 326
Built environment variables					
Population density	per square mile	13 521	6996	1748	33 911
Number of household units	–	14 164	12 449	759	63 952
Median house value	US dollar	265 713	124 461	97 086	652 888
Jobs per household	–	0.9119	1.8443	0.0046	12.91
Distance to the nearest transit stop	m	280	64	146	444
Violent crime density	per 100,000 population per year	2919	2078	299	10 348
Property crime density	per 100,000 population per year	14 038	9835	1507	47 583
Intersection density	per square mile	177	80	84	617
Transit frequency	per hour	511	736	14	4622
Walkability index	–	14.22	1.15	11.81	17.60
Road density	miles per square mile	61	38	4	257
Sidewalk density	miles per square mile	110	60	7	314
Transit stop density	per square mile	75	57	5	298



(a) E-scooter Sharing (b) Ridesourcing

Fig. 1. Spatial distributions of E-scooter sharing and ridesourcing trips. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

2022 in our study and aggregated the data by day. The spatial and temporal distributions of e-scooter sharing and ridesourcing trips are presented in Figs. 1 and 2. Note that in Fig. 1, the colors of the lines represent the number of trips between origin–destination pairs.

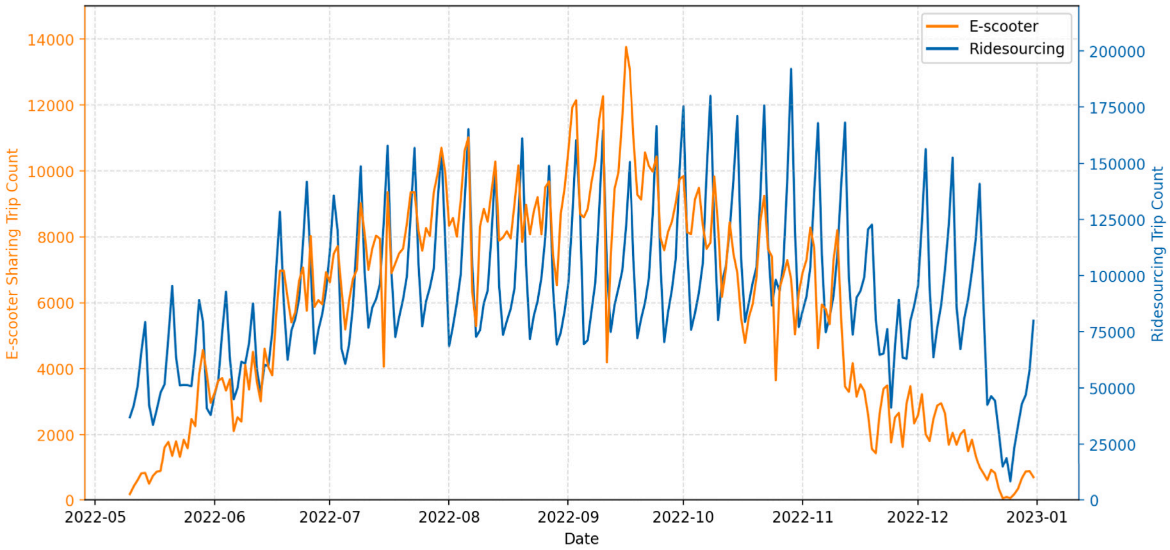


Fig. 2. Temporal distributions of E-scooter sharing and ridesourcing trips. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

We obtained the socio-demographic data in Chicago from the American Community Survey (ACS) 2017–2022 5-year estimates. The socio-demographic variables were collected at census-tract-level and then aggregated to Community Areas. These community-area-level variables included the percentage of female population, the percentage of population aged 18–35, the percentage of white population, the percentage of black population, the percentage of population with bachelor's degree and above, unemployment rate, the percentage of household with vehicle, and median household income. We calculated these community-area-level variables using the population-weighted average of census-tract-level variables.

The built environment data was collected from the Smart Location Database version 3.0[2] and the Chicago Data Portal. These variables included population density, the number of household units, median house values, jobs per household, violent crime density, property crime density, intersection density, transit frequency, and the national walkability index. Some built environment variables cannot be directly collected from these sources, including road network density, sidewalk density, and transit stop density. We used GIS tools to calculate these variables. Specifically, we first collected the road network and sidewalk data for Chicago. Then we conducted spatial joins via GIS tools to calculate the total length of road network and sidewalk in each area. These lengths were then divided by the respective areas to compute the densities. Similarly, for the transit stop density, we collected the locations of transit stops, performed a spatial join to determine the count of stops in each area, and calculated the density by dividing this count by the area. The built environment variables were collected or calculated at the community-area level.

5. Results

5.1. SHAP values summary

Fig. 3 illustrates the distribution of SHAP values for each feature. Each point represents an instance. The red color represents large feature values, while the blue color reflects small values. The position of features on the y-axis is ordered according to their SHAP feature importance.

In Fig. 3, red points representing ridesourcing trip counts were allocated to the right side of the axis to exhibit high SHAP values, implying that increased ridesourcing usage made a positive contribution to estimating e-scooter usage. This result suggests that areas with frequent ridesourcing service utilization were more likely to experience intense usage of shared e-scooters. Similarly, instances with smaller fare differences, more jobs per household, higher proportion of the young population, lower proportion of the white population, higher population density, higher proportion of household with vehicle, higher median household income and house value, higher road and transit stop density, and lower violent crime density, were more likely to witness more e-scooter sharing trips. The percentage of population with bachelor's degree and above was negatively associated with shared e-scooter usage. This result contradicts findings from some existing studies (Merlin et al., 2021; Bai and Jiao, 2020; Jiao and Bai, 2020) but consists with survey-based studies suggesting that highly educated individuals were less willing to use shared e-scooters (Blazanin et al., 2022; Araghi et al., 2022). Some features had mixed effects on shared e-scooter usage, such as percentage of female population,

[2] https://www.epa.gov/smartgrowth/smart-location-mapping#SLD.

Fig. 3. SHAP summary plot. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

percentage of black population, and distance to the nearest transit stop. These features displayed mixed distributions of blue points and red points, indicating mixed associations with shared e-scooter usage. For example, instances with a moderate percentage of the female population (indicated by purple dots) displayed significant positive and negative Shapley values. Conversely, instances with high or low female percentages (red and blue dots, respectively) showed Shapley values clustering around zero, indicating a more significant effect of moderate female population percentages on e-scooter usage.

5.2. SHAP feature importance

5.2.1. Overall feature importance

Fig. 4 displays the SHAP feature importance of each feature in estimating e-scooter sharing usage. Ridesourcing trip count emerged as the most influential factor among all features. Other noteworthy contributors in the top 20 include fare difference, built environment aspects (such as number of jobs per household, population density, and violent crime density) and socio-demographic elements (such as age, education level, and gender) related to trip origins or destinations. In contrast, the design factors, such as intersection density and sidewalk density, played a less significant role in the estimation.

5.2.2. Feature importance of ridesourcing trip count in different spatial context

To reveal the spatial heterogeneity of the relevance between e-scooter sharing and ridesourcing, we further examined the feature importance of ridesourcing trip count in different spatial contexts, including both built environment factors and socio-demographic characteristics. The results are presented in Fig. 5. Note that the feature importance variations of a variable measured at trip origin and trip destination exhibited similar patterns. Therefore, we only present results at trip origins in Fig. 5.

In Fig. 5, the *x*-axis represents the values of the spatial context variables, and the *y*-axis depicts the SHAP feature importance of ridesourcing trip count, represented by the absolute SHAP value of ridesourcing trip count. The boxplots illustrate the distribution of the feature importance, with the main box covering the range from the lower quartile (Q1) to the upper quartile (Q3) of the dataset. The whiskers stretch out from this box, reaching up to the most distant data point that is within 1.5 times the inter-quartile range (IQR), measured from either edge of the box. The orange line indicates the median value, the green dashed line signifies the mean value, and the notches around the median illustrate the confidence interval. SHAP feature importance quantifies the contribution

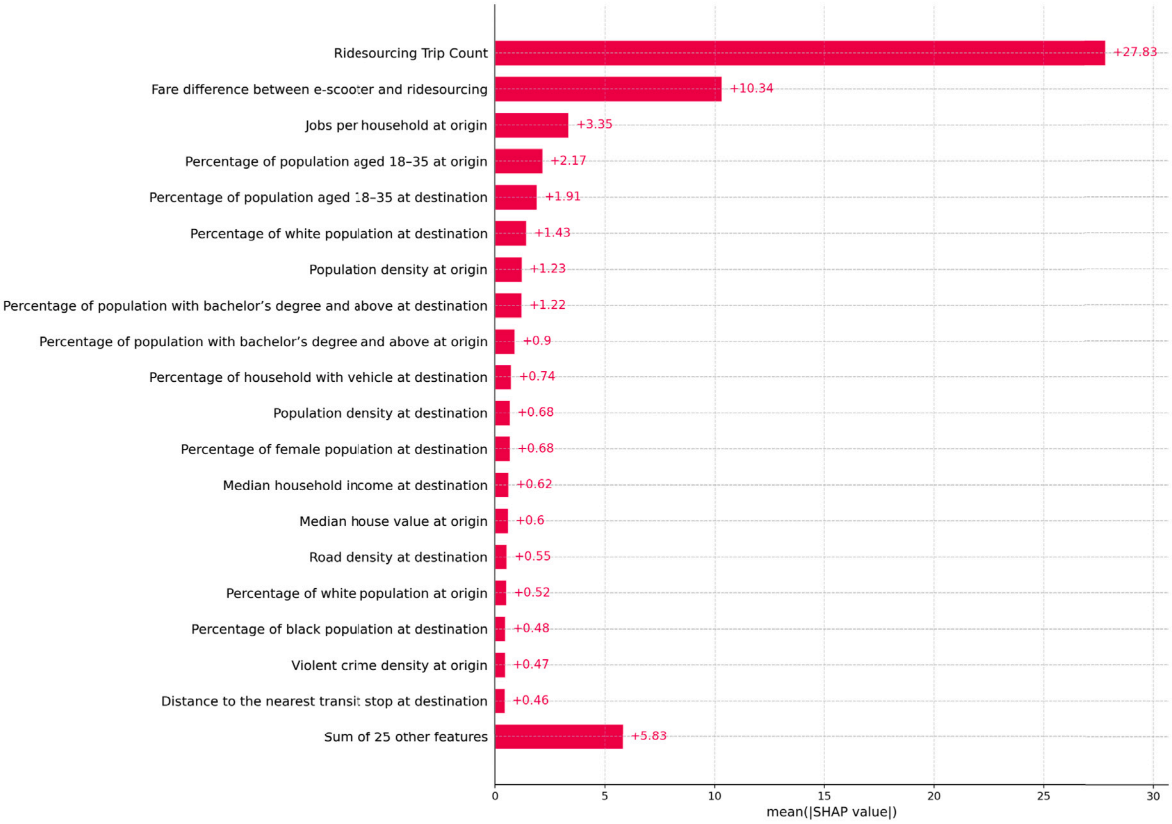


Fig. 4. SHAP feature importance plot.

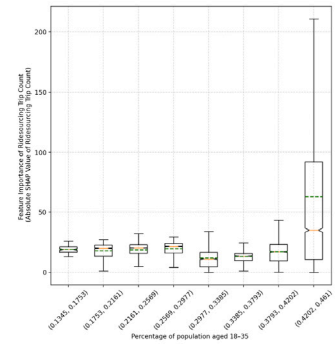
of a feature to the model estimation. A high feature importance for an independent variable indicates that a change in its value significantly influences the model's output (i.e., e-scooter sharing trip count).

The relevance between e-scooter sharing and ridesourcing varies in areas with different socio-demographic factors. According to Fig. 5(a), the influence of ridesourcing on shared e-scooters usage is much more significant in areas with a high proportion (over 42%) of young population. In areas with a proportion of young population below 42%, the impact of ridesourcing on shared e-scooter usage is similar, while the influence is slightly insignificant in areas with a young population proportion between 30% and 38%. Fig. 5(b) illustrates an interesting phenomenon that the association between e-scooter sharing and ridesourcing decreases as the proportion of the population with bachelor's degree and above increases from 3% to 41%. Subsequently, the association increases as the proportion rises from 41% to 63%. The variance of the association also increases with the proportion. Fig. 5(c) shows the impacts of ridesourcing on e-scooter sharing are more significant when the unemployment rate is below 3.8%. The impacts are also slightly more pronounced in areas with an unemployment rate between 7.8% and 11.7%. These results are largely attributed to the correlation between a high education level and a low unemployment rate, as well as the ample supply of ridesourcing and e-scooter sharing services (Merlin et al., 2021; Xu et al., 2021; Bai and Jiao, 2020). Areas with a white population proportion above 68% and areas with a female population proportion between 51.15% and 52.35% also exhibit high associations between e-scooter sharing and ridesourcing (Figs. 5(d) and 5(e)).

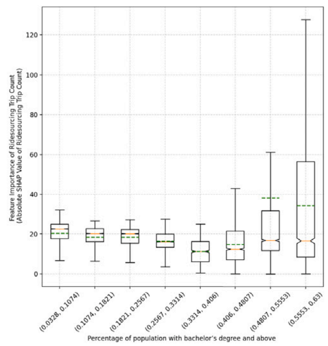
Built environment characteristics can also affect the relevance between e-scooter sharing and ridesourcing. Fig. 5(f) shows that the connection between e-scooter sharing and ridesourcing is more conspicuous in areas with a population density above 13 192 per square mile, particularly within the range of 13 192 to 16 053 per square mile. The variability of their association in these areas is also greater. From Fig. 5(g), we can find that the relevance between e-scooter sharing and ridesourcing is high in areas with a number of jobs per household between 1.04 and 1.39, and the relevance is quite similar in other areas. Fig. 5(h) shows that in areas with violent crime density between 5257 to 6083 per 100,000 population per year, the relevance between e-scooter sharing and ridesourcing is significantly high, while the relevance is weak in other areas.

5.3. SHAP interaction values for ridesourcing and key variables

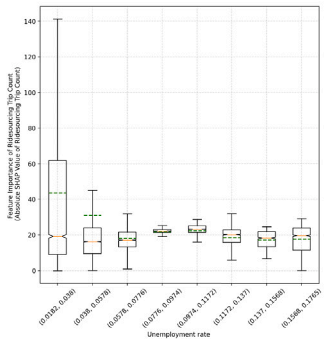
As illustrated in Section 3.2, we use colored scatter plots to depict SHAP interaction values for ridesourcing and key variables. The results are presented in Fig. 7. Note that the SHAP interaction values of a variable, measured at trip origin and trip destination,



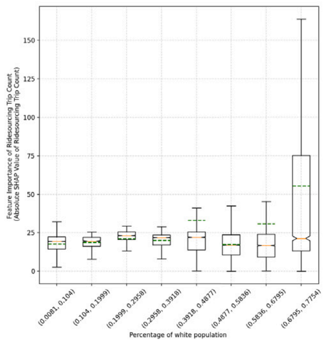
(a) Young Population Proportion



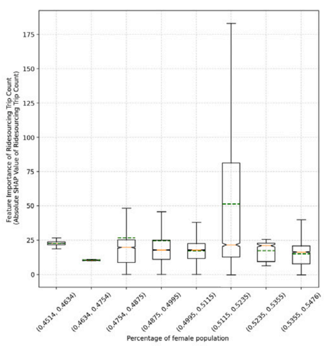
(b) Proportion of Population with Bachelor's Degree and Above



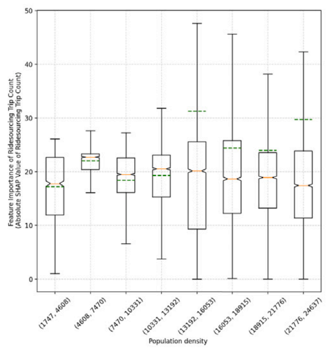
(c) Unemployment Rate



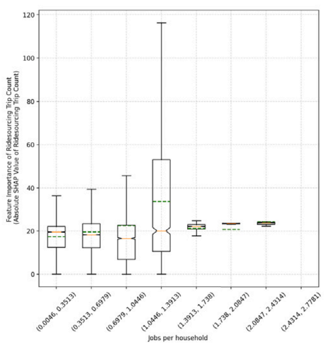
(d) White Population Proportion



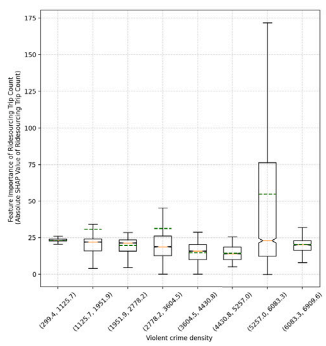
(e) Female Population Proportion



(f) Population Density



(g) Number of Jobs per Household



(h) Violent Crime Density

Fig. 5. Feature importance of ridesourcing trip count in different spatial contexts.

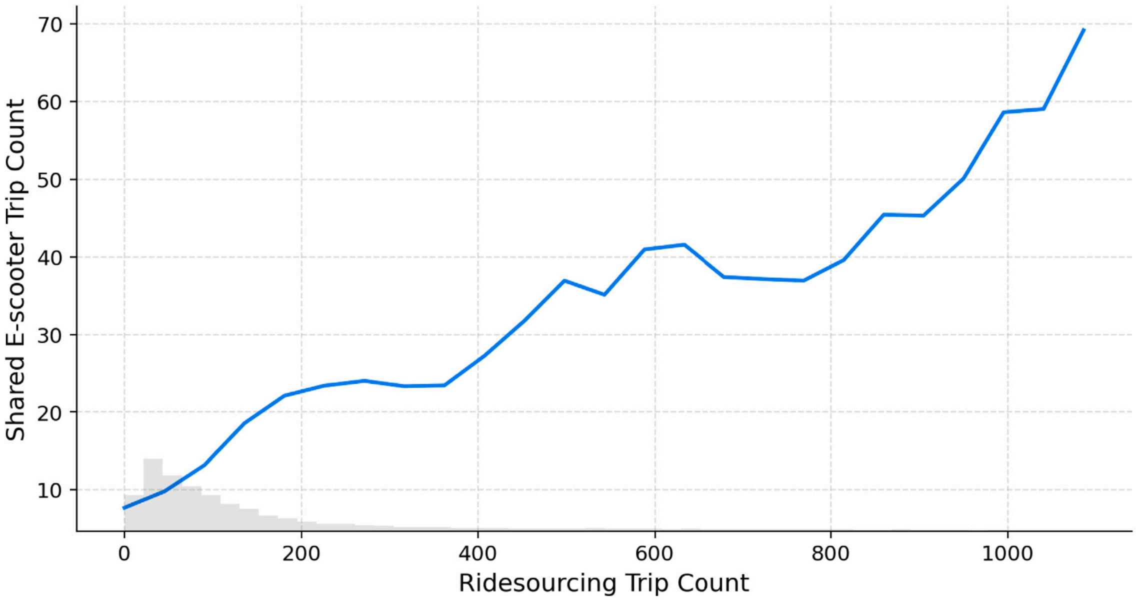


Fig. 6. Partial dependence plot for ridesourcing trip count.

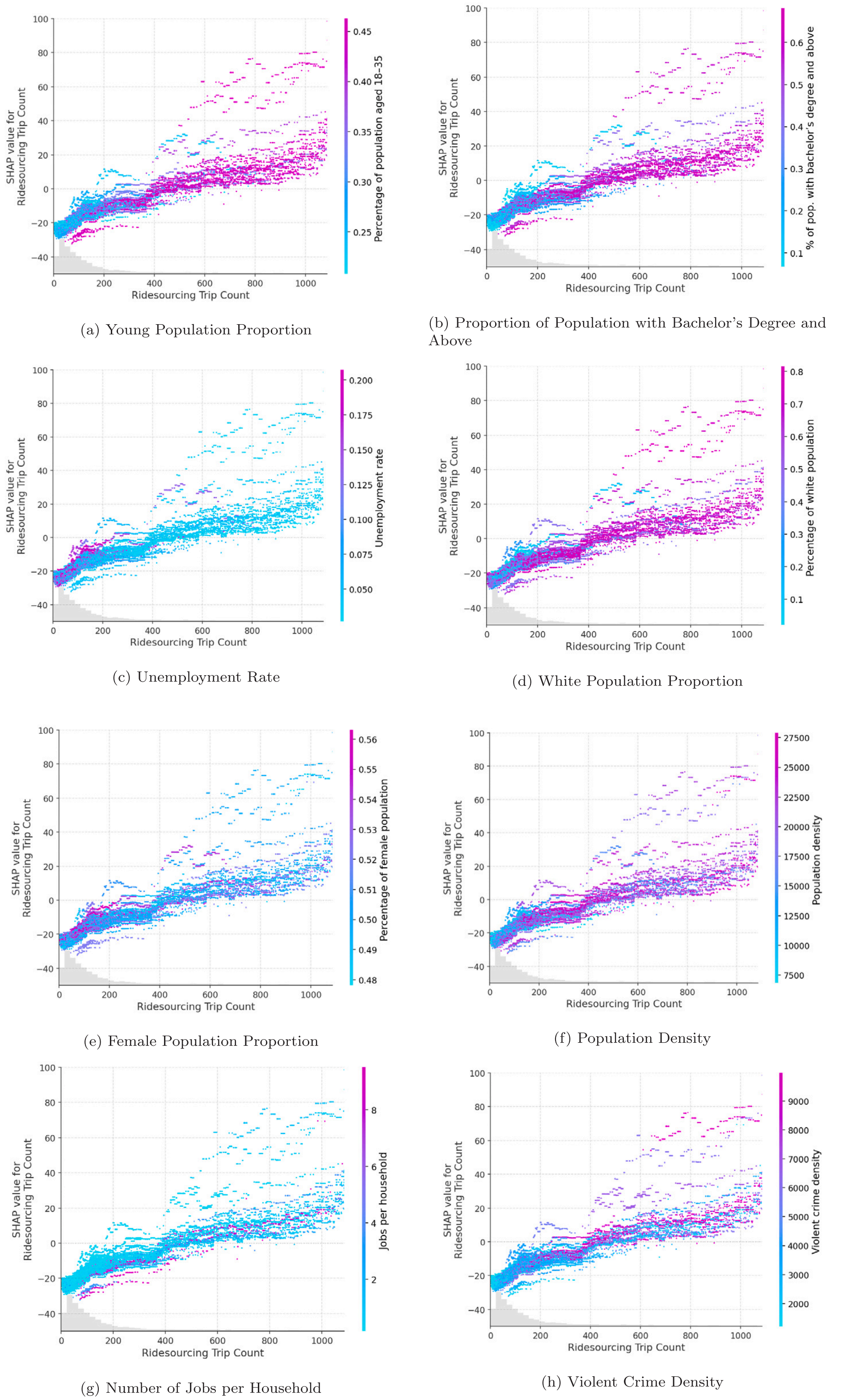
displayed similar patterns. Therefore, we only present the results at trip origins in Fig. 7. In addition, to better understand the relationship between ridesourcing and e-scooter sharing, we present a partial dependence plot (PDP) for ridesourcing trip count in Fig. 6 and discuss it first.

Partial dependence plot reveals the marginal effect of a specific feature on model estimation (Friedman, 2001; Molnar, 2020). In Fig. 6, the x-axis represents ridesourcing trip count, the y-axis is e-scooter sharing trip, and the histogram indicates the data distribution. Fig. 6 shows a non-linear relationship between ridesourcing and e-scooter sharing usage (usage is represented by trip count). As the number of ridesourcing trips increases from 0 to around 200, the usage of e-scooter sharing also rises rapidly. This growth stabilizes, and the curve flattens when the ridesourcing trip count ranges from 200 to 350 and again from 500 to 800. Notably, e-scooter usage experiences accelerated growth as ridesourcing trips further increase from 350 to 500 and from 800 to 1000. These results indicate that community-area-level shared e-scooter usage is positively related to ridesourcing. Furthermore, in community areas with moderate demand for ridesourcing services, the use of shared e-scooters appears to be less influenced by ridesourcing. This trend could stem from disparities in accessibility between e-scooter sharing and ridesourcing services in these regions: e-scooter sharing tends to have limited accessibility, whereas ridesourcing services are more readily accessible. Another reason could be that people in these areas are less willing to use e-scooter sharing. E-scooter sharing is less competitive than ridesourcing in these community areas.

We further explore the non-linear relationship between e-scooter sharing and ridesourcing in different spatial contexts using SHAP interaction values (Fig. 7). The x-axis is ridesourcing trip count. The y-axis on the left denotes the SHAP value for ridesourcing usage, representing the impacts of ridesourcing usage on e-scooter usage. The histogram illustrates ridesourcing trip count distribution. The color bar on the right shows measurements of the corresponding spatial context. The findings are articulated for each figure, grouped by socio-demographic characteristics and built environment characteristics.

For areas with a small proportion of the young population (Fig. 7(a)), the shared e-scooter usage increased fast as ridesourcing trip counts increased from 0 to around 200. The trend remained steady for ridesourcing trips ranging between 200 and 400, then it increased slowly as ridesourcing trip counts increased from 400. Areas with a large portion of young people seemed to increase steadily without evident threshold effects. The increasing trends indicate that e-scooters are popular among young people (Bai and Jiao, 2020; Jiao and Bai, 2020). The continuously increasing e-scooter usage in areas with a relatively high proportion of the young population reflected a larger willingness to use e-scooters for people living in those areas. Shown in Fig. 7(b), areas with a low proportion of the population with bachelor's, denoted by blue points, present a trend with a significant threshold effect after ridesourcing trips exceeded 200. Similar threshold effects can be found for trends formed by areas with a high unemployment rate (Fig. 7(c)). The trends formed by areas with low or high white populations increased steadily, showing no evident disparities (Fig. 7(d)). No evident difference was shown in trends for areas with low or high female population proportions (Fig. 7(e)).

Shown in Fig. 7(f), blue points represent instances with low population density, and purple points represent those with high population density. The trend formed by blue points showed that the shared e-scooter usage increased fast as ridesourcing trip counts increased from 0 to around 100. The shared e-scooter usage increased slowly as ridesourcing trip counts increased from 100 to 1000. In contrast, the trend formed by purple points presented to increase steadily. It indicates a significant threshold effect of the ridesourcing trip counts on e-scooter usage among areas with small population density. As shown in Fig. 7(g), the trend formed



(a) Young Population Proportion

(b) Proportion of Population with Bachelor's Degree and Above

(c) Unemployment Rate

(d) White Population Proportion

(e) Female Population Proportion

(f) Population Density

(g) Number of Jobs per Household

(h) Violent Crime Density

Fig. 7. SHAP interaction values: Ridesourcing vs. Key variables. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

by blue points increased fast as ridesourcing trip counts increased from 0 to around 150, and it increased slowly as ridesourcing trip counts increased from 250 to 1000, representing a significant threshold effect. At the same time, the trend formed by purple points that represent areas with more jobs per household presented steadily increasing. It indicates that e-scooter usage is more sensitive to the local usage of ridesourcing services in areas with fewer jobs per household than in areas with more jobs per household. Violent crime density did not show to impact the trend, as the trends formed by blue and purple points almost overlap (Fig. 7(h)).

6. Discussion

The results indicated that instances with smaller fare differences, more jobs per household, higher proportion of the young population, lower proportion of the white population, higher population density, higher proportion of household with vehicle, higher median household income and house value, higher road and transit stop density, and lower violent crime density, were more likely to have more e-scooter sharing trips. These results aligned with existing survey-based studies and trip-based studies (Lee et al., 2021a; Cao et al., 2021; Bai and Jiao, 2020; Mitra and Hess, 2021; Christoforou et al., 2021; Laa and Leth, 2020; Sanders et al., 2020; Zhao et al., 2022; Jiao and Bai, 2020; Merlin et al., 2021). Interestingly, the percentage of population with bachelor's degree and above was negatively associated with shared e-scooter usage. This result contradicts findings from some existing studies (Merlin et al., 2021; Bai and Jiao, 2020; Jiao and Bai, 2020) but consists with survey-based studies suggesting that highly educated individuals were less willing to use shared e-scooters (Blazanin et al., 2022; Araghi et al., 2022). A possible explanation is that highly educated people tend to be more health-conscious and may view shared e-scooter as a competing mode to active travel mode such as walking and biking (Blazanin et al., 2022). Furthermore, targeted city initiatives have made shared e-scooters more appealing to those with a high school education or less (Araghi et al., 2022).

Some features had mixed effects on shared e-scooter usage, such as percentage of female population, percentage of black population, and distance to the nearest transit stop. For example, instances with a moderate percentage of the female population displayed significant positive and negative Shapley values, indicating a more significant effect of moderate female population percentages on e-scooter usage. When using SHAP values to estimate the importance of a feature, a high feature importance does not necessarily indicate whether the effect of that feature on the outcome variable is distinctly positive or negative. Instead, it shows the magnitude of the feature's impact on the model's predictions, regardless of the direction of that impact. Some features might exhibit mixed effects where they increase the dependent variable in some cases and decrease it in others. This is often the case in complex models where interactions between features play a significant role. Even if a feature has a high importance score, it might contribute both positively and negatively across different instances. Previous studies have not thoroughly explored these mixed effects.

The influence of ridesourcing on shared e-scooters usage is much more significant in areas with a high proportion of young population. These results align with the findings of prior research indicating that young people are more willing to use both ridesourcing and e-scooter sharing (Aguilera-García et al., 2022; Azimi et al., 2022; Ghaffar et al., 2020; Yan et al., 2020; Bai and Jiao, 2020; Jiao and Bai, 2020; Nikiforiadis et al., 2021; Yang et al., 2021). The association between e-scooter sharing and ridesourcing is more significant in areas with high population densities. It is because areas with high population density usually have larger travel demand, better accessibility to ridesourcing and e-scooter sharing, and more flexible travel mode choices (Cervero and Kockelman, 1997; Ghaffar et al., 2020; Bai and Jiao, 2020; Cervero, 2002).

Trends with an evident threshold effect represent a lack of willingness to use e-scooters or limited accessibility (ridesourcing trips increase while e-scooter sharing trips do not). Seen from Figs. 7(a) and 7(b), e-scooter sharing usage in areas with a large portion of young people and those with an advanced degree seemed to increase steadily without evident threshold effects. These results indicated that areas with large percentages of young population and those with an advanced degree present strong adoption of e-scooters. These results align with existing studies indicating young and high-educated individuals are more willing to use e-scooter sharing (Nikiforiadis et al., 2021; Blazanin et al., 2022; Bai and Jiao, 2020; Cao et al., 2021).

These findings can assist cities in harmonizing e-scooter sharing and ridesourcing, thus promoting sustainable transportation systems. First, the threshold effect in e-scooter sharing's association with ridesourcing tends to result from the limited competitiveness of e-scooter sharing in these areas. To promote e-scooter sharing, cities could work with shared e-scooter operators to improve its accessibility and adoption (i.e., people's willingness to use e-scooter sharing). Specifically, cities and operators could improve the density and quality of biking facilities, allocate more e-scooter vehicles to these communities, and modify pricing strategies to attract more shared e-scooter users. Second, cities could pay more attention to areas where e-scooter sharing and ridesourcing have significant relevance (measured by feature importance) and large variance (revealed by SHAP interaction value plot). In these areas, e-scooter sharing is more sensitive to changes in ridesourcing usage, and the impact is more complicated. In other words, a change in ridesourcing is more likely to trigger a more uncertain change in e-scooter sharing. Making policies for these areas should be more careful, and the policies should be less aggressive to avoid excessive competition between these two travel modes.

7. Conclusion

This study explored the spatial heterogeneity of e-scooter's relationship with ridesourcing using LightGBM and SHAP. Unlike previous studies that used categorical variables to represent the relationship between e-scooter sharing and ridesourcing, this study filled the research gap by incorporating ridesourcing usage in the independent variables to model e-scooter sharing usage. It then used SHAP Interaction Values to examine the influence of each spatial variable on the relationship. Specifically, we used the daily ridesourcing usage along with a list of socio-demographic and built environment variables to model the daily usage of e-scooter sharing. We then analyzed the SHAP Interaction Values for ridesourcing and key spatial variables to understand e-scooter' relationship with ridesourcing in different spatial contexts.

The results suggested that the feature importance of ridesourcing in estimating shared e-scooter usage varied in areas with different socio-demographic and built environment characteristics. The association between e-scooter sharing and ridesourcing is more significant in areas with large population density, a moderate number of jobs per household, a low unemployment rate, and a high proportion of young population, white population, and population with bachelor's degree and above.

The e-scooter sharing usage was positively related to ridesourcing at the community-area-level, and their association was non-linear. In areas with moderate ridesourcing demand, e-scooter sharing tends to be less sensitive to changes in ridesourcing trip count, indicating limited competitiveness of e-scooter sharing in these areas. These nonlinearities in their relationship also varied across different spatial contexts. The threshold effects were less significant in areas with large population density, more jobs per household, low unemployment rate, and high proportion of young people, white population, and population with advanced degrees, where people were more willing to use e-scooter sharing.

It is worth noting that this study examines the relationship between e-scooters and ridesourcing using aggregate-level data, specifically at the Community Area and Origin-Destination (O–D) pair levels. While analyzing travel behavior using disaggregated data is generally more effective for drawing more convincing causal inferences, aggregate-level analysis, as employed in this study, offers distinct advantages. Notably, it significantly reduces data acquisition costs and minimizes concerns about sampling bias, which can arise from inadequate sample sizes or lack of representativeness.

Several issues require future research. First, while our focus was on applying and interpreting a single model, further studies should apply and interpret additional machine learning models to validate the results. Second, this research did not differentiate the interaction between e-scooters and ridesourcing during weekdays versus weekends, or peak hours versus non-peak hours. Given the distinct traveler needs and behavior patterns during different times, future investigations should consider these temporal variations. Third, perceived safety factors can influence e-scooter sharing usage. However, we face challenges in collecting data that accurately reflect perceived safety and flexibility at a regional level. Future research could delve deeper into this aspect to provide more comprehensive insights. Lastly, the findings specific to Chicago may not universally apply to cities with differing characteristics. Hence, assessing the transferability of these results to other urban contexts is an important area for future study.

CRediT authorship contribution statement

Junfeng Jiao: Writing – review & editing, Supervision, Resources, Project administration, Funding acquisition, Conceptualization. **Yiming Xu:** Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Yang Li:** Writing – review & editing, Writing – original draft, Methodology, Investigation, Formal analysis, Conceptualization.

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.

Declaration of Generative AI and AI-assisted technologies in the writing process

During the preparation of this work the authors used ChatGPT in order to improve readability and language. After using this tool/service, the authors reviewed and edited the content as needed and take full responsibility for the content of the publication.

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