Spatio-temporal Heterogeneity Analysis of Transportation Equity Based on GTWR

Shihui Hu
Beijing University of Chemical Technology
Beijing, China
2021040276@buct.edu.cn

Xinmeng Wan*
Beijing Normal University
Beijing, China
202321081061@mail.bnu.edu.cn

Danhuai Guo†
Spatial Intelligent Research Lab, College of Information Science and TechnologyBeijing University of Chemical Technology
Beijing, China
gdh@buct.edu.cn

ABSTRACT

Online car-hailing services have become increasingly popular for their convenience and efficiency. However, this trend has presented challenges for the elderly population, who may struggle with smartphone usage and thus face difficulties accessing these services. This issue has the potential to worsen existing traffic inequalities. To address this issue, this paper analysis the spatial and temporal heterogeneity of urban transportation pattern of Chengdu City by utilizing traffic flow data and various sources of information such as online car-hailing order data and POI data. The LDA model has been employed to extract semantic and spatial-temporal information from ride-hailing users, which is then integrated into an enhanced spectral clustering algorithm to identify the specific needs of the elderly population. Furthermore, a travel equity index has been established to evaluate the fairness of travel opportunities. The study also investigates the spatio-temporal variations in travel difficulties faced by the elderly group and explores the diversity of factors that influence travel equity using the GTWR regression model. The research findings provide valuable insights into whether the current transportation infrastructure adequately caters to the travel requirements of the elderly group and offer effective recommendations for future transportation planning.

CCS CONCEPTS

• **Social and professional topics** → **Seniors**.

KEYWORDS

Spatial and temporal Heterogeneity, Traffic equality, Spatio-temporal geographical weighted regression model, Multi-source data

*Both first authors contributed equally to this research.
†Corresponding author

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1 INTRODUCTION

The diversification of travel demand and travel modes, including the emergence of online car-hailing platforms, has undoubtedly brought convenience and efficiency to urban transportation. These platforms allow users to hail a car online, providing flexible pick-up and drop-off locations and times. This has improved the overall efficiency of transportation and balanced taxi resources, reducing the number of empty taxis on the road.

However, it is crucial to consider the impact of technological advancements on certain segments of the population, particularly the elderly or vulnerable individuals who may not be proficient in using smartphones or accessing online services. The rise of online car-hailing services has presented challenges for these groups, making it more difficult for them to access traditional taxi services. This issue raises concerns about fairness and social security, underscoring the importance of ensuring that transportation services remain accessible to all members of society, regardless of their technological proficiency. Efforts should be focused on addressing the digital divide and providing alternative means for these individuals to access transportation services. Possible solutions may include dedicated phone lines or call centers for those unable to use smartphone applications, training programs to enhance digital literacy among the elderly, or partnerships with community organizations to offer assistance in booking rides for those in need. Overall, while online car-hailing platforms have undoubtedly improved transportation efficiency, it is crucial to address the challenges faced by certain segments of the population to ensure equitable access to transportation.

2 RELATED WORKS

2.1 Transportation equity

Transportation equity is a crucial aspect of traffic research, playing a significant role in achieving social equity and demanding careful consideration in urban traffic planning. Despite the absence of a universally accepted definition, researchers generally agree on four levels of transportation equity[5]: horizontal, vertical, opportunity, and result. Horizontal equity pertains to the fair allocation of resources among individuals or groups with similar needs, while vertical equity focuses on the disparities in resources between different groups or individuals. Equality of opportunity ensures that all individuals have equal access to public transportation, while result equality allows travelers to choose transportation modes according to their circumstances, resulting in varied outcomes for each group or individual.

Evaluating transportation fairness involves assessing the distribution and utilization of transportation resources in different regions, the time required to access the same resources, and the economic benefits generated by these resources. These dimensions of fairness are interconnected and should be considered holistically rather than in isolation. Therefore, achieving transportation equity necessitates a balanced allocation of resources both between and within groups, within reasonable limits. True transportation equity is achieved when result equality is realized while maintaining equal opportunities. Various methods exist to evaluate traffic fairness, including spatial equilibrium, GIS-based fairness measurement methods, the SRAI evaluation framework, Wilson entropy theory, and the Lotka-Volterra model, among others.

2.2 Taxi data modeling analysis

In recent years, there has been a notable increase in the number of researchers conducting spatio-temporal scale analysis using taxi data. These researchers have been employing various modeling tools such as data mining and machine learning to quantitatively analyze the supply and demand of taxi resources from different perspectives. For instance, Loecher utilized the Empirical Bayes model to explain the uncertainty surrounding taxi supply and demand by identifying hot spots for getting on and off the bus, and further analyzed the characteristics of these regions [6]. Similarly, Li employed the BP neural network model to define the balance parameters of taxi supply and demand based on taxi driving speed, and explored its spatio-temporal evolution. However, it is worth noting that the aforementioned studies primarily focused on analyzing specific regions where transportation imbalances are particularly severe, and there is a lack of research on other areas. In contrast, Kamga's findings demonstrated relevance in the number of passengers, the range of taxis driven, the distance traveled by taxis, as well as other influencing factors such as time of day and weather .[4] However, most of the existing papers mainly discuss the demand and supply of taxis, without conducting an overall analysis of the relationship between taxi supply and demand. On a similar note, Yang [10]identified factors related to taxi supply and demand using taxi GPS data to measure the degree of imbalance between taxi supply and demand in terms of time and space. However, there is a need for more in-depth analysis of the factors that affect the balance of taxi supply and demand.

Most studies on taxi supply and demand focuses on solutions related to the real-time ratio of vehicle availability within short time frames. However, there is still insufficient research and discussion on areas where supply and demand imbalances frequently occur. Additionally, studies on taxi supply and demand often approach the topic from a global perspective, lacking specific analyses of the challenges faced by the elderly during their rides. Few articles directly address the fairness of elderly mobility.

3 DATA DESCRIPTION

3.1 Data source

3.1.1 POI Data. POI (Point of Interest) data includes office buildings, schools, parking lots and other types of point of interest data. The point of interest data used in this paper is obtained from OpenStreetMap(OSM) API, which is an open mapping collaboration that provides mapping information to websites, mobile applications, client software, and more. The raw dataset includes categories such as schools, town halls, distinctive buildings and shopping spending. There are about 620,000 points of interest data in Chengdu, and the data fields are composed of name, location, administrative region and category, as shown in the Table 1.

Table 1: Example of POI data

Name	Longitude	Latitude	Region	Category
Temple	104.29100	30.49868	Longquanyi	Attraction
Railway	104.35606	30.51455	Longquanyi	Transportation
Clinic	104.35051	30.50214	Longquanyi	Healthcare

3.1.2 Road network data. The road network data is from OSM too. And the open source mapping service is regularly checked for accuracy and timeliness. The 2016 data of Chengdu road network OSM is shown in the Figure 1.

Figure 1: Example of road network data

3.1.3 Demographic data. The population data comes from Global Human Settlement Layer (GHSL) project hosted by the European Union. GHSL generates building maps, population density maps and other forms of information using data mining techniques, which provides global spatial information on human activities (https://ghsl.jrc.ec.europa.eu/). The GHS-POP spatial raster dataset describes the distribution of world population in different years. It is based on administrative unit census data, breaking down the population distribution data into grid data based on the distribution and density of buildings around the world over the same period. We selects the population network data of 2015 with a resolution of 250 meters.

3.1.4 Taxi transactions data. The full-volume taxi demand data is retrieved from the ride-hailing data of Didi platform in Chengdu in August 2016,including itinerant taxi, online car, private car and other full taxi. There are about 8000 pieces of longitude and latitude coordinate data for daily demand points, and about 500 pieces for each time point, as shown in the Table 2.

Table 2: Example of the full-scale taxi demand data

Time	Longitude	Latitude	Demand
2016/8/8 0:00	104.0881	30.6660	4
2016/8/8 0:00	103.6453	30.9870	3
2016/8/8 0:00	104.0380	30.5877	11

3.2 Research area

3.2.1 Determination of research area. Visualize the starting point in the daily order data, as shown in the figure. We can see that more than 85% of the car location information is located in the downtown area of Chengdu, so we choose this area as the research area of this paper.

Figure 2: The administrative division of the research area

3.2.2 Division of time. Since the operation of taxi is closely related to time[2], it is necessary to divide the data of the whole day from the time dimension. The conventional method is to divide the time into 24×1 hours and explore the characteristics of each hour's taxi. In addition, the type of day should also be taken into account. Previous studies have shown that the difference between working days, weekends and holidays has also had an impact on the identification of taxi supply and demand.

3.2.3 Division of space. The method of space division in this study is the grid method. The determined space area of Chengdu city center is divided into ordered grid units of fixed size based on the definition to form a grid structure to divide the research area, which is used for statistical analysis of order quantity, POI quantity and other factors. Compared with other partitioning methods, grid method is more intuitive and easy to understand, which also has high computational efficiency in a large range of spatial areas. This paper divides the research area into 1000m*1000m, as shown in the Figure 3.

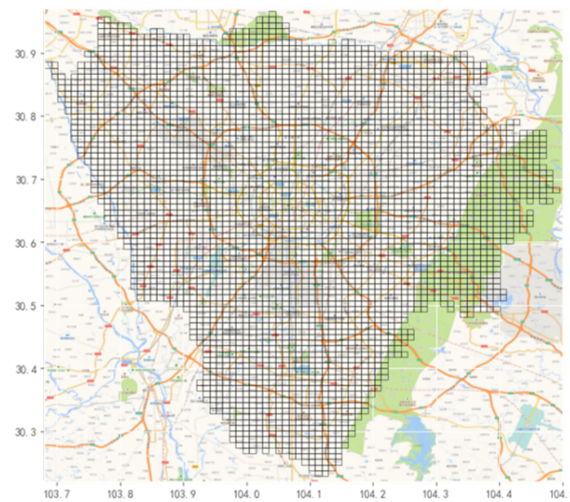

Figure 3: Grid visualization of the research area

3.3 Data processing

3.3.1 POI Data. The original POI data categories are intricate, with major categories containing multiple subcategories, leading to overlapping and intersecting types. Consequently, a reclassification of the POI data is necessary. After consulting relevant literature, this paper adheres to the principles of universality and consistency in POI classification to undertake the reclassification.

While each point of interest has an impact on a certain demographic, some types of POIs may have lower public awareness. These less recognized points of interest may not significantly contribute to the functional representation of the region. Therefore, they are excluded. The selection process focuses on POI data that distinctly represents grid functional features, such as pedestrian streets representing shopping consumption and higher education institutions representing science, education, and culture. Building upon the reclassification, the study conducted a quantitative analysis of the various types of POIs within the grids of the research area. However, utilizing quantity alone as the weight for a particular POI type is not reasonable. It is essential to consider the spatial distribution of POIs across different grids. To address this issue, the research employs the TF-IDF method from text mining to measure the weights of POIs.

$$TFIDF_{ij} = \ln(TF_{ij}) \times IDF_i \tag{1}$$

$$IDF_i = \lg \frac{D}{\{j: t_i \in d_j\}} \tag{2}$$

In the equation, $TFIDF_{ij}$represents the weight of the i-th type of point of interest in grid j; TF_{ij} denotes the quantity of the i-th type of point of interest in grid j; IDF_{ij} signifies the inverse document frequency of the i-th type of point of interest; D represents the total number of all grids; $\{j{:}t_i \in d_j\}$ indicates the number of grids containing the i-th type of point of interest.

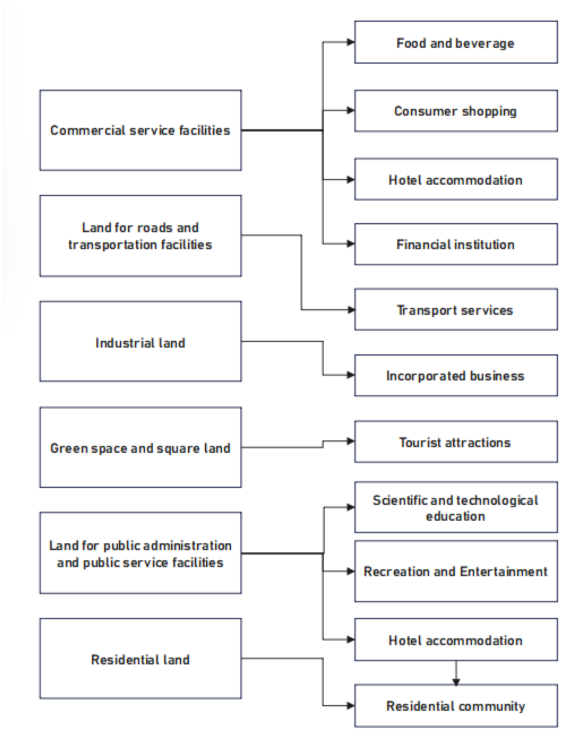

Figure 4: The Final Classification Map of POI Data

3.3.2 Road network data. For Chengdu's vector road network data and grid data, the study calculates the main road network density and secondary road network density within each regional grid. These densities serve as the road network features for each region.

3.3.3 Demographic data. The original data has a resolution inconsistent with the grid size set for the study. Therefore, the grid data with a resolution of 250 meters is resampled to match the resolution of the grid. This resampled data is used as the population feature for each region. We defined people over the age of 60 as the elderly as our study population. Given that this study focuses on the ease of travel by the elderly using circular taxi services, the elderly population in each grid is calculated by considering the proportion of each age group to the total population, based on the results of the seventh national population census for the respective district and county divisions.

4 METHOD

4.1 Spatial and temporal heterogeneity of transportation

When examining transportation equity, the methods used to assess it can differ depending on the research question at hand. In the case of the challenges faced by the elderly in hailing taxis, it is important to note that the overall demand for taxi services among the elderly has remained relatively stable. However, as ride-hailing services continue to expand, there may be a decrease in the number of traditional taxis available. Despite this, it is worth highlighting that the majority of elderly individuals still prefer hailing traditional taxis, particularly those that utilize traditional hand-signaling methods. Therefore, when analyzing the problem, the equity of the elderly population in hailing traditional taxis can be defined as follows.

$$\mathrm{G}(\mathrm{s_i}, \mathrm{t_i}) = 1 - \frac{\mathrm{O}(\mathrm{s_i}, \mathrm{t_i})}{T\,(s_i, t_i)} \tag{3}$$

$\mathbf{s_i}, \mathbf{t_i}$represent the coordinates of sample points in different space-time, $\mathrm{T}(\mathrm{s_i}, \mathrm{t_i})$is the total demand for taxi services by the elderly at the i-th sample point, $\mathrm{O}(\mathrm{s_i}, \mathrm{t_i})$is the demand for ride-hailing services by the elderly at the i-th sample point, and $\mathrm{G}(\mathrm{s_i}, \mathrm{t_i})$ is the level of difficulty for the elderly population at the i-th sample point in hailing traditional taxis (hereinafter referred to as travel difficulty).

According to research findings [1] on the travel habits of the elderly population, a calculation method has been established to determine their demand for taxi travel. The method is defined by Equation (4),

$$\mathrm{T}(\mathrm{s_i}, \mathrm{t_i}) = \sigma \times \mathrm{P}(\mathrm{s_i},) \times \mathrm{H}(\mathrm{t_i}) \times \mathrm{D}(\mathrm{s_i}, \mathrm{t_i}) \quad \mathrm{i} = 1, 2, \ldots, \mathrm{n} \tag{4}$$

$\mathbf{s_i}, \mathbf{t_i}$ represent the coordinates of sample points in different space-time, $\mathbf{P}(\mathbf{s_i},)$ is the proportion of elderly people at the i-th sample point, $\mathbf{H}(\mathbf{s_i},)$ is the temporal parameter for elderly travel at the i-th sample point, $\mathrm{D}(\mathrm{s_i}, \mathrm{t_i})$ is the total taxi demand for all age groups at the i-th sample point, and σ is an adjustment parameter. By substituting these parameters and taxi travel data into Equation (4), the demand data $\mathrm{T}(\mathrm{s_i}, \mathrm{t_i})$ for taxi travel by the elderly population is obtained. Furthermore, Equation (3) is employed to calculate travel difficulty, and the resulting data is analyzed to ensure equitable considerations.

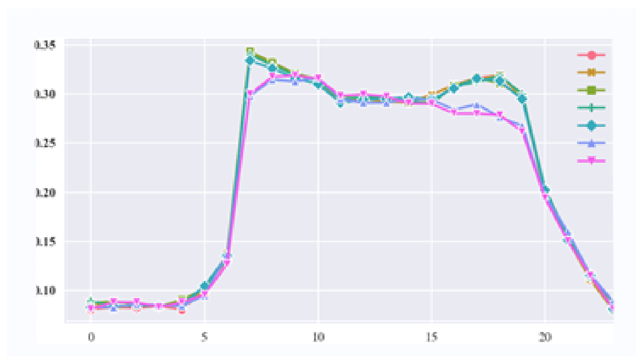

Figure 5: The distribution curve of taxi-hailing difficulty for elderly individuals.

4.1.1 Temporal Heterogeneity Analysis. (1) During the weekdays, there is a noticeable pattern and similarity in the difficulty faced by elderly individuals when trying to hail a taxi. There are two concentrated peaks of difficulty within a day, namely during the morning rush hour and the daytime lull. However, as the day progresses and it becomes evening and nighttime, the difficulty in hailing a taxi decreases.

(2) On weekends, the trend of difficulty remains consistent, with a single peak of taxi-hailing difficulty throughout the day. It is worth noting that elderly people face challenges in transportation

during weekends without a distinct morning or evening peak, and the difficulty in hailing a taxi remains high during the daytime.

4.1.2 Spatial Heterogeneity Analysis. A heatmap has been generated to illustrate the average travel difficulty experienced by elderly individuals within grid regions. The red-colored grid cells on the heatmap indicate areas with higher travel difficulty. Upon analysis, it is evident that the elevated travel difficulty is predominantly concentrated within the Chengdu Fourth Ring Road. Specifically, commercial districts and residential zones with high population density exhibit higher levels of travel difficulty. This could be attributed to factors such as limited accessibility and inadequate infrastructure for elderly individuals. In contrast, other regions display lower travel difficulty, possibly due to higher pedestrian traffic and increased mobility in these areas. The heatmap provides valuable insights into the spatial distribution of travel difficulty for elderly individuals, facilitating the identification of areas that require targeted interventions to improve accessibility and mobility.

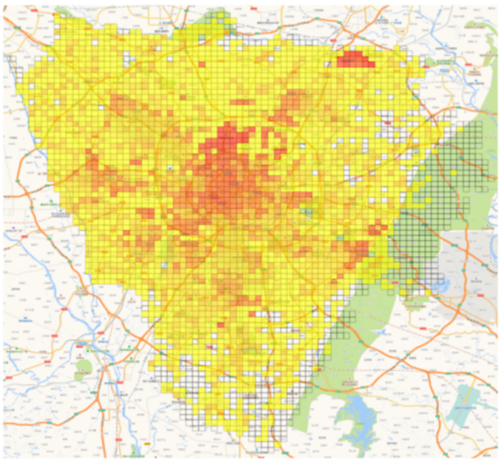

Figure 6: The spatial distribution of taxi-hailing difficulty for elderly individuals.

Spatial factors play a significant role in determining travel difficulties for elderly individuals, as evidenced by the distinct characteristics exhibited by different grid cells. The presence of diverse land use patterns across various urban regions further exacerbates the imbalance in transportation ease for this demographic. These findings highlight the need for targeted interventions and improvements in infrastructure to ensure that elderly individuals can navigate their surroundings with minimal challenges and maintain their independence.

4.2 Geographically Weighted Regression model

Spatio-Temporal heterogeneity refers to the variability and complexity of certain elements in their temporal and spatial distributions, with manifestations differing according to the type of data. In regression models, the Ordinary Least Squares (OLS) model is commonly used[9], but it fails to capture the spatial attributes of variables as its coefficients are unique across the entire spatial extent of the study. To address this limitation and formulate a more comprehensive regression model, some scholars have incorporated the geographical location information of variables into the computation of regression coefficients, resulting in the development of the Geographically Weighted Regression (GWR) model[1]. However, scholars have also recognized the importance of considering the temporal characteristics of variables in practical research questions. Consequently, they have integrated temporal factors into the construction of regression models, leading to the emergence of the Geographically and Temporally Weighted Regression (GTWR) model.[3]

(1) OLS model

$$\mathbf{y} = \beta_0 + \beta_1 \mathbf{x}_1 + \beta_2 \mathbf{x}_2 + \cdots \ldots \beta_\mathrm{p} \mathbf{x}_\mathrm{p} + \varepsilon \tag{5}$$

$\beta_0, \beta_1, \beta_2 \ldots\ldots \beta_\mathrm{p}$represent the coefficients of the independent variables; $\mathrm{x}_1, \mathrm{x}_2 \ldots\ldots \mathrm{x}_\mathrm{p}$refer to the independent variables; ϵ denotes the error term.

(2) GWR model

The GWR model integrates geographical location information into the OLS model.

$$y_i = \beta_0(u_i, v_i) + \sum_k \beta_k(u_i, v_i) x_{ik} + \varepsilon_i \quad i = 1, 2, \ldots\ldots n \tag{6}$$

$(\mathrm{u_i}, \mathrm{v_i})$represents the spatial characteristics of the grid; $\mathrm{x_{ik}}$ is the variable value of the kth influencing factor for the ith grid, and $\beta_\mathrm{k}(\mathrm{u_i}, \mathrm{v_i})$ is the regression coefficient of the kth influencing factor for the ith grid.

(3) GTWR model

The GTWR model incorporates the factor of time on the basis of GWR.

$$y_i = \beta_0(u_i, v_i, t_i) + \sum_k \beta_k(u_i, v_i, t_i) x_{ik} + \xi_i \quad i = 1, 2, \ldots\ldots n \tag{7}$$

$(\mathrm{u_i}, \mathrm{v_i}, \mathrm{t_i})$ denote the coordinates of different grids with respect to time; $\mathrm{x_{ik}}$ represents the value of the k-th explanatory variable at sample point i; n indicates the presence of n sample points; the coefficient $\beta_\mathrm{k}(\mathrm{u_i}, \mathrm{v_i}, \mathrm{t_i})$ represents the regression coefficient of the k-th independent variable for the i-th sample point; ξ_i is the random error for the i-th sample point.

4.3 Model evaluation metrics

(1) Coefficient of determination R^2

$$R^2 = 1 - \frac{\sum(Y_{actual} - Y_{predict})^2}{\sum(Y_{actual} - Y_{mean})^2} \tag{8}$$

The coefficient of determination, with values ranging from 0 to 1, indicates the explanatory power of the fitted equation—the larger the value, the stronger the explanatory capability.

(2) AICc (Akaike Information Criterion corrected for small sample sizes)

$$\mathrm{AIC} = \mathrm{e}^{\left(\frac{2\mathrm{K}}{\mathrm{T}}\right)} \frac{\sum_{\mathrm{t}=1}^{\mathrm{T}} \mathrm{e}_\mathrm{t}^2}{\mathrm{T}} \tag{9}$$

$$\mathrm{AICc} = \mathrm{AIC} + \frac{2\mathrm{k}(\mathrm{k}+1)}{\mathrm{n}-\mathrm{k}-1} \tag{10}$$

$\mathrm{e}^{\left(\frac{2\mathrm{K}}{\mathrm{T}}\right)}$ serves as a penalty factor, where k is the number of parameters, and n is the number of observations. The better the model fit, the smaller the AICc value.

(3) RSS (Residual Sum of Squares)

The regression model provides a means to estimate the difficulty level faced by elderly individuals when taking taxis in different time and spatial contexts. By comparing these estimates to the actual values, we can calculate the Residual Sum of Squares (RSS), which represents the sum of the squared differences between the estimated and actual values. A smaller RSS value indicates a higher level of explanatory power for the model, suggesting a better fit between the estimated and actual difficulty levels.

4.4 Variable selection and multicollinearity testing

Previous studies have extensively examined various factors that influence taxi demand, such as population density and urban functionality. In this particular study, we aim to build upon existing research by integrating relevant findings and analyzing the difficulty faced by elderly individuals in Chengdu when attempting to schedule taxi rides at different times and locations. To achieve this, we will consider the aforementioned issue as the dependent variable and explore potential influencing factors from three distinct perspectives: socio-economic, transportation, and built environment. By adopting a comprehensive approach, we hope to contribute valuable insights to the field and enhance our understanding of the challenges faced by the elderly population in accessing taxi services in Chengdu.

When constructing a regression model, it is important to assess the relationship between independent variables to ensure the validity and reliability of the model. This is done through the multicollinearity test, which examines the presence of correlation among variables. The commonly used variance inflation factor (VIF) is employed for this purpose. [8]

$$\mathrm{VIF} = \frac{1}{1-\mathrm{r}^2}$$

The VIF is calculated using the coefficient of linear regression, with a higher value indicating a greater likelihood of collinearity among explanatory variables. Generally, when the VIF falls between 0 and 10, it is considered that there is no high collinearity among independent variables, satisfying the conditions for regression analysis.

The test results indicate that the VIF values for the significant variables shown in Table 4 are all between 0 and 10, and there is no collinearity among them. Therefore, these variables can be considered as independent variables in the regression model.

5 RESULTS

5.1 Regression results

he objective of this study is to analyze the difficulty of taxi travel in different grids of Chengdu at various time periods during the day. This difficulty is considered as the dependent variable, while the selected significant variables are treated as independent variables for spatiotemporal geographically weighted regression analysis.

To provide a descriptive analysis of the regression coefficients for each influencing factor, five statistical measures are employed - minimum, minimum quartile, median, maximum quartile, and maximum. A positive fitted coefficient indicates a promoting effect of the explanatory variable on the dependent variable, with a larger absolute value indicating a more pronounced effect. Conversely, a negative fitted coefficient indicates an inhibitory effect.[7]

In addition, the evaluation metric $R^2$is 0.862, indicating that the GTWR model has a good fit.

Table 3: Results of the independent variable tests

Feature types	Features	Definition
Socio-economic attributes	X1	Elderly population count
Transportation-related attributes	X2	Number of bus stops
	X3	Number of subway stations
Built environment-related attributes	X4	Density of main road networks
	X5	Density of secondary road networks
	X6	Weight of transportation facility POI
	X7	Weight of leisure and entertainment POI
	X8	Weight of corporate and business POI
	X9	Weight of healthcare POI
	X10	Weight of residential community POI
	X11	Weight of tourist attraction POI
	X12	Weight of science, education, and cultural POI
	X13	Weight of shopping and consumption POI
	X14	Weight of hotel and accommodation POI
	X15	Weight of financial institution POI
	X16	Weight of dining and culinary POI

Table 4: Results of the independent variable tests

Significant variables	Value of t	Significance
X1	5.872	0
X2	1.531	0
X4	8.798	0
X5	3.532	0
X9	3.908	0.003
X10	2.855	0.004
X13	3.109	0.002

5.2 Performance evaluation

We select OLS model and GWR model as baseline.

Table 5: Comparison of Model Fit Goodness

	minimum	1/4	1/2	3/4	maximum
Population density	-0.01438	0.00428	0.01371	0.0248	0.05361
Number of bus stops	-0.35619	-0.03462	0.04711	0.13748	0.24782
Density of main road networks	-0.00061	0.00053	0.00061	0.00146	0.00247
Density of secondary road networks	-0.00226	-0.00042	-0.00017	0.00011	0.00246
Weight of healthcare POI	-0.25372	-0.06172	0.06494	0.02423	0.27529
Weight of residential community POI	-0.35273	0.01732	0.12839	0.16728	0.52398
Weight of shopping and consumption POI	-0.12832	0.09782	0.13829	0.15832	0.32742

Table 6: Performance comparison of models

	R^2	AICc	RSS
OLS	0.721	813.3	1835.6
GWR	0.754	578.2	1327.4
GTWR	0.862	122.1	903.5

Based on the analysis conducted, it is evident that the GTWR model stands out with its superior performance compared to the GWR and OLS models. This conclusion is supported by the smallest values of AICc and RSS obtained by the GTWR model. Additionally, the R^2 value of the GTWR model surpasses that of both the GWR and OLS models. Taking into account the temporal and spatial characteristics of the variables under consideration, it can be confidently stated that the GTWR model exhibits the highest level of performance.

5.3 Influencing factors analysis

The mobility of the elderly is influenced by a variety of factors, and it is important to understand how these factors change over time and across different locations. This study recognizes the spatiotemporal non-stationarity inherent in these influencing factors and aims to provide an accurate visualization and analysis of their temporal evolution and spatial characteristics. To achieve this, the regression coefficients of selected factors have been visualized, allowing for a comprehensive understanding of their impact on the mobility of the elderly. By examining these coefficients, researchers and policymakers can gain valuable insights into the dynamics of elderly mobility and make informed decisions to improve the quality of life for this population.

(1) Temporal Heterogeneity Analysis

The analysis of temporal heterogeneity of influencing factors was conducted through the use of box plots. Figure 9 visually illustrates the changing trend of regression coefficients within the time range from 7 a.m. to 10 a.m. The box plot sequence provides valuable insights into the variability and distribution of these coefficients over time. By examining the graphical representation, patterns and fluctuations in the influencing factors can be identified and further analyzed. This analysis aids in understanding the temporal dynamics and potential correlations between the factors under investigation.

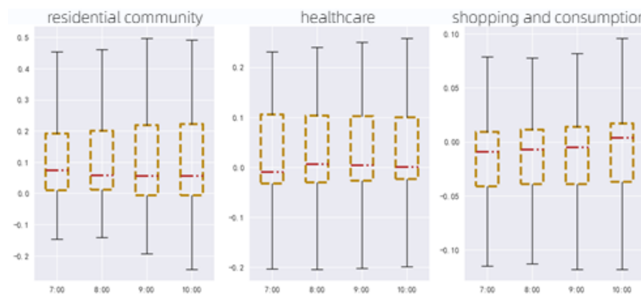

Figure 7: Temporal distribution of regression coefficients for travel difficulty

The analysis of the regression coefficients for various influencing factors reveals that there are both positive and negative changes in direction and magnitude, indicating variations in their impact on travel difficulty for each spatial unit within the four-hour period.

When examining each influencing factor individually, it is observed that the impact of shopping consumption displays a noticeable upward trend over the four hours. The descriptive statistical index values of the regression coefficients reach their maximum during the fourth time period. This suggests that the density of shopping consumption points has both a promoting and inhibiting effect on travel difficulty, with a growing trend.

Furthermore, the impact of medical services on travel difficulty slightly increases during the first two time periods and then gradually decreases. This indicates a promotion effect that initially rises and then falls.

The influence of residential areas exhibits different temporal trends. In general, both positive and negative impacts on travel difficulty show an increasing trend, with both inhibitory and promoting effects gradually strengthening. This leads to a more pronounced polarization phenomenon.

(2) Spatial Heterogeneity Analysis

In analyzing the influence of different independent variables on travel difficulty in various spatial locations, it becomes evident that there are distinct mechanisms at play. For instance, when considering healthcare, residential areas, and shopping consumption points of interest (POI) weights, we can visualize the regression coefficients of influencing factors within each spatial unit to gain a better understanding. It is important to note that the impact of independent variables on travel difficulty differs across spatial locations.

By conducting a single-factor analysis, we find that regions where residential areas have a strong positive impact on travel difficulty are primarily concentrated in the core areas of Chengdu's Third Ring Road and the central area of Shuangliu District, such as the central urban areas. This can be attributed to the higher concentration of residential areas in these regions and the extensive coverage of rail transit stations, making them more appealing for travel.

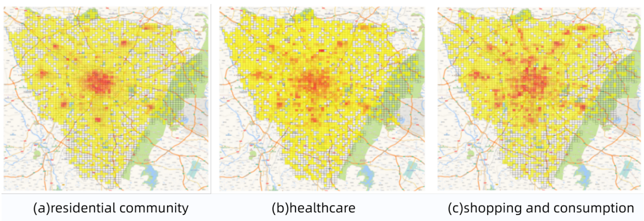

Figure 8: Spatial distribution of regression coefficients for travel difficulty

On the other hand, areas where healthcare services have a significant enhancing effect on travel difficulty are mainly found in the main urban areas and regions connected to the central urban area. This can be explained by the abundance of medical facilities and a dense population in these areas, resulting in a higher demand for travel.

Furthermore, the density of shopping consumption points within the fourth ring road and along major roads has the strongest positive impact on travel difficulty, with the fitted coefficients reaching their peak. The regions affected by this positive effect are widespread. This can be attributed to the wide distribution of shopping interest points such as malls and supermarkets, along with a well-developed rail transit network, resulting in overall higher demand among the elderly population.

6 CONCLUSION

This article addresses the pressing issue of accommodating the transportation needs of the elderly population, particularly in relation to their ability to catch taxis under varying spatiotemporal conditions. By combining demand data for elderly individuals using taxis and order data for those utilizing ride-hailing services, a comprehensive assessment is conducted to gauge the challenges they encounter. A fairness analysis is carried out from both temporal and spatial perspectives, shedding light on the factors contributing to the difficulty of catching a circular taxi. To further delve into this issue, a spatiotemporal geographically weighted regression (GTWR) model is established, enabling a detailed analysis of the influencing factors. The findings derived from this study provide valuable insights into the underlying reasons behind the unfairness experienced by elderly individuals in their travel experiences from different perspectives.

As the global elderly population continues to grow, society is confronted with the significant challenge of catering to their transportation needs. Ensuring a positive travel experience for the elderly is a crucial aspect of promoting social equity. By prioritizing the travel experience of the elderly, we not only contribute to achieving transportation equity, but also enhance social security as a whole. Addressing the transportation challenges faced by the elderly is an essential step towards creating a more inclusive and equitable urban transportation system.

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