Exploring the spatial differences in travel mode choice of rail transit in Chongqing

Lixun Liu [1,2*], Adam Dennett [3], Robin Hickman [4]

1 School of Architecture and Planning, Hunan University, Changsha 410082, China

2 Hunan Key Laboratory of Sciences of Urban and Rural Human Settlements in Hilly Areas, Hunan University, Changsha 410082, China

3 Centre for Advanced Spatial Analysis, University College London

4 Bartlett School of Planning, University College London

Corresponding author

E-mail address: liulixun@hnu.edu.cn

Authors' ORCID：

Lixun Liu: 0000-0001-5990-2699

Adam Dennett: 0000-0001-8036-0185

Robin Hickman：0000-0002-5410-6594

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Abstract

People's use of the rail transit system varies over space. Previous literature suggests there is a social equity dimension in the distribution of benefits from new urban transit systems, but how this varies spatially is poorly evidenced. The research aims to examine the spatial differences in the use of rail transit and associated transport equity. Using a case study of Chongqing, a geographically weighted regression (GWR) model is used to reveal the spatial variation in parameter estimates, complementing the traditional multivariate global model. The analysis demonstrates the effect of rail transit in facilitating people's travel and mitigating transport-related social inequity, including for those with mobility disadvantages and living in areas with poor access to public transport. The results emphasise the necessity of associated development strategies and transport policies in favour of socially disadvantaged groups, such as low fare levels. Implications for planning interventions are proposed based on the model results.

Key words：

Travel mode choice; rail transit; spatial differences; GWR; social equity

1. Introduction

The Chinese government has put forward 'achieving common prosperity for everyone' as the goal of the 14th Five-Year Plan (2021-2025). Transport planning has an important role to play in this, and the development of public transport is encouraged by increasing network coverage and accessibility. The needs of residents living in remote areas and those with mobility disadvantages are especially emphasised, with the social role of public transport perceived as important to the integration of society. A critical issue in Chinese cities is to consider how rail transit systems impact on people's mobility and accessibility with social-spatial variations, since huge investment is being spent on transit systems. An increasing network coverage is important, but also access to the transit system and use of this is important for different population cohorts.

Investments in new urban transit systems are expected to have positive impacts across a city, indeed this

is often assumed by policymakers. There is an emerging body of evidence suggesting that the developmental effects associated with urban transit systems exert different types of impact, not only on geographic locations, but also on the mobility and accessibility of different population groups (Jones 2015, Nilsson et al. 2020, Liu, Dennett, et al. 2023). However, a number of perceived gaps exist in the previous research. First, how people use rail transit varies across space. The spatial context is critical to these impacts, with cities having different built forms and neighbourhoods where particular resident cohorts are located (Geurs et al. 2019). Rail transit has a differential impact on facilitating people's travel. In some contexts, new rail lines play a limited role in facilitating established residents' travel patterns (Lane et al. 2004), while elsewhere the rail transit system provides new public transport services for socially disadvantaged groups (Zhao and Li 2019). Meanwhile, whether rail transit promotes people's travel in a socially equitable way is a critical dimension of new rail investment, but is often poorly understood. Furthermore, there may be associated development strategies and policies essential to adopt to achieve greater equity, but again these are lacking in supportive evidence.

The research aims to examine the spatial variation in the mode choice of rail transit and associated transport-related equity. In order to achieve the research aim, the paper addresses the following questions progressively. First, how do the relationships between the social economic and travel characteristic variables and people's transit mode choice vary over space? Second, with social-spatial variations in travel patterns, do transport equity issues arise and what is the role of rail transit in facilitating transport inequity? Third, what planning strategies can be adopted for promoting people's use of rail transit in different areas of the city? We examine these issues by exploring people's use of urban rail transit for commuting in Chongqing, China. A multivariate regression is used to produce a global model of the association between influential variables and people's rail transit use. A Geographically Weighted Regression (GWR) model (Fotheringham et al. 2003) is then used to account for the spatial variation in model parameter estimates.

The study hence contributes to the literature in the following ways: it shows how the spatial variations of influential factors on people's transit mode choice exist, and can be identified using GWR. It demonstrates the important role of the rail transit system in facilitating travel in areas where a high level of established residents and rural migrants are concentrated, including for those without a car. Rail transit

development in the old city to some extent alleviates the transport-related social inequity. Furthermore, a dense transit network and good accessibility to the station should be enhanced to promote transit use, such as surrounding mixed use and a walkable environment, facilitating last-mile connectivity for disadvantaged groups' access to the stations, especially for the elderly. Associated planning strategies need to reflect these considerations and seek to encourage more equitable access. Transit fare levels are also considered as a supporting policy mechanism for transit usage across income groups.

2. Literature review

2.1 Determinants of travel mode choice and the role of rail transit

It is widely understood that there are built environment, attitudinal and socio-economic factors related to travel mode choice (Hickman et al. 2009), but that the relationships vary much by context (Hickman et al. 2015). Travel characteristics themselves impact on the mode choice (Liu, Wang, et al. 2023). For example, individuals have a stronger preference for rail transit or driving over other travel modes when their trip distance gets longer (Limtanakool et al. 2006). Longer travel time might be expected due to longer distances but are compensated by higher mean travel speeds which are often achieved by making use of travel modes such as private cars or regional rail networks (Scheiner 2010). The spatial determinants of transit use are well researched. Ewing and Cervero (2010) provide an overview, examining the role of density, diversity (mix of use), neighbourhood design, destination accessibility and distance to transit in relation to travel. Shen (2016) finds that proximity to Metro stations has a significant association with the choice of rail transit, alongside income, employment status and a longer commute distance, reflecting that transit-supported urban expansion is likely to lead to environmentally sustainable travel behaviours. Similarly, home proximity to rail transit stations has a significant positive association with transit mode choice (Zhao 2013, Ding et al. 2017).

Rail transit is hence used as a tool to promote accessibility to activities. It is suggested that public transport-related development has an important role to enhance destination options for low income and suburban residents (Zhao and Li 2016), as employment and service facilities are attracted around the transit nodes. However, Wang (2020) compared the relationships between income differences and

accessibility, and found low-income groups have a significant lower level of overall access to public transit and commercial facilities. Therefore, the physical accessibility to the transit system and affordability of cost and time may have an influence on the distribution of transport accessibility and resulting travel behaviours. Hence, there is emerging research examining accessibility and the social equity impacts of transit investment. This can be further developed, particularly in the Chinese context.

2.2 Impact of socio-economic characteristics and associated transport equity

Multiple socio-economic characteristics interact with travel mode choice (Geurs et al. 2009, Jones and Lucas 2012). For example, with the Jubilee Line Extension in London, the critical factors influencing travel mode shift were those relating to income, car ownership, education level, age and perceptions (Lane et al. 2004). Residential status (e.g. newcomers vs. established residents) is important; the newcomers in the JLE-impacted areas were more likely to be: younger, white, employed, highly qualified, earn much higher incomes and be car owners. In this context, it is generally the newcomers who benefit from the improved travel accessibility, and use the new system for accessing employment and other activities. The established residents living in the area made relatively limited use of the JLE, and there was minimal evidence of any changes to expand travel patterns (Gatersleben et al. 2007, Butler 2007). But, this finding is likely to differ much by context – whether the rail transit system is used by all groups in society requires more evidence, again including from the Chinese context.

Individual travel choice, and how this is impacted by socio-economic factors is not well researched in Chinese studies (Wang and Zhou 2017). Since the 1990s, rural to urban migration has become the impetus for the development boom in China. Newcomers and established residents in China tend to live in particular neighbourhoods in cities, changing over time. The greatest division of social characteristics is not only the economic status but the Chinese Hukou system. The Hukou system is a means of population registration, which identifies the holder is a legal resident of a particular area. An individual's Hukou can be either urban or rural. The urban Hukou system determines that a person can enjoy subsidised public services, such as health care and education in the city, from which rural Hukou holders are excluded. Hukou status is important in exploring travel behaviours as it can reduce the chances of members of migrant families from travelling to particular activities and increase the time cost of

commuting (Zhao and Howden-Chapman 2010). Income and Hukou are identified by researchers as significant predictors of public transport mode choice or wider travel (Pan et al. 2009, Creemers et al. 2012). However, it is likely that mobility disadvantages can result from a combination of several social economic characteristics, such as age, car ownership and Hukou, and vary spatially across the city. A more comprehensive analysis using multiple socio-economic and other factors is thus needed to explore the social equity dimensions of rail transit use.

2.3 Modelling spatial varying effects

Spatial and social factors may actually reinforce one another to impact on people's travel patterns. There have been limited studies considering spatial variations of people's travel behaviour in China (Yang et al. 2017, Li et al. 2019). Only a few studies have discussed the policy implications related to the spatial variation of influencing determinants on transit ridership (Li et al. 2020). Aggregate level-analysis, say at the city level, can also overlook spatial variation at the local neighbourhood scales. A more detailed analysis would allow more spatial disparities to be explored. GWR models have been utilised especially to address the potential spatial dependency and model spatial heterogeneity in data relationships across space (Brunsdon et al. 1996). In the field of transport, GWR has also been used to explore the spatial variation of travel behaviours and public transport use (Cardozo et al. 2012, Chiou et al. 2015, Özbil Torun et al. 2020), but there are very limited applications in relation to transport-related social equity. A study exploring commuting inequity and its determinants in Shanghai, utilizing GWR, discovers that disadvantaged areas characterised by low rent or poor job accessibility tend to be inhabited by large numbers of workers with long commutes. This suggests inclusive transport policy should concern individual people's capability to use the transport services, beyond providing public transit services (Zhao and Cao 2020). Spatial variations in people's travel behaviours can be explored further to reveal the related equity issues.

This paper draws on these perceived research gaps, examining urban growth and transit usage, including socio-economic and spatial differentiation across Chongqing, hence contributes to the emerging evidence in this field.

3. Methodology

3.1 Survey method

Chongqing is used as the case study for analysis. As of the 2014 Census, the main urban area has a residential population of 8.2 million. The old city region in Chongqing is the peninsula surrounded by Yangzi River and Jialing River. The old city centre is located at the junction of the two rivers. With the development of the airport in the early 1990s, development has grown at astonishing speed, turning the previous farmlands on the north of the river into a prosperous new city region within just 20 years (Figure 1). By 2017, four lines of the public transit Metro network are in operation in Chongqing (lines 1, 2, 3 and 6), with a total length of 202 km. The first line was opened in 2004. Three new lines were added, two in 2011 and one in 2012, and there is now an extensive Metro network.

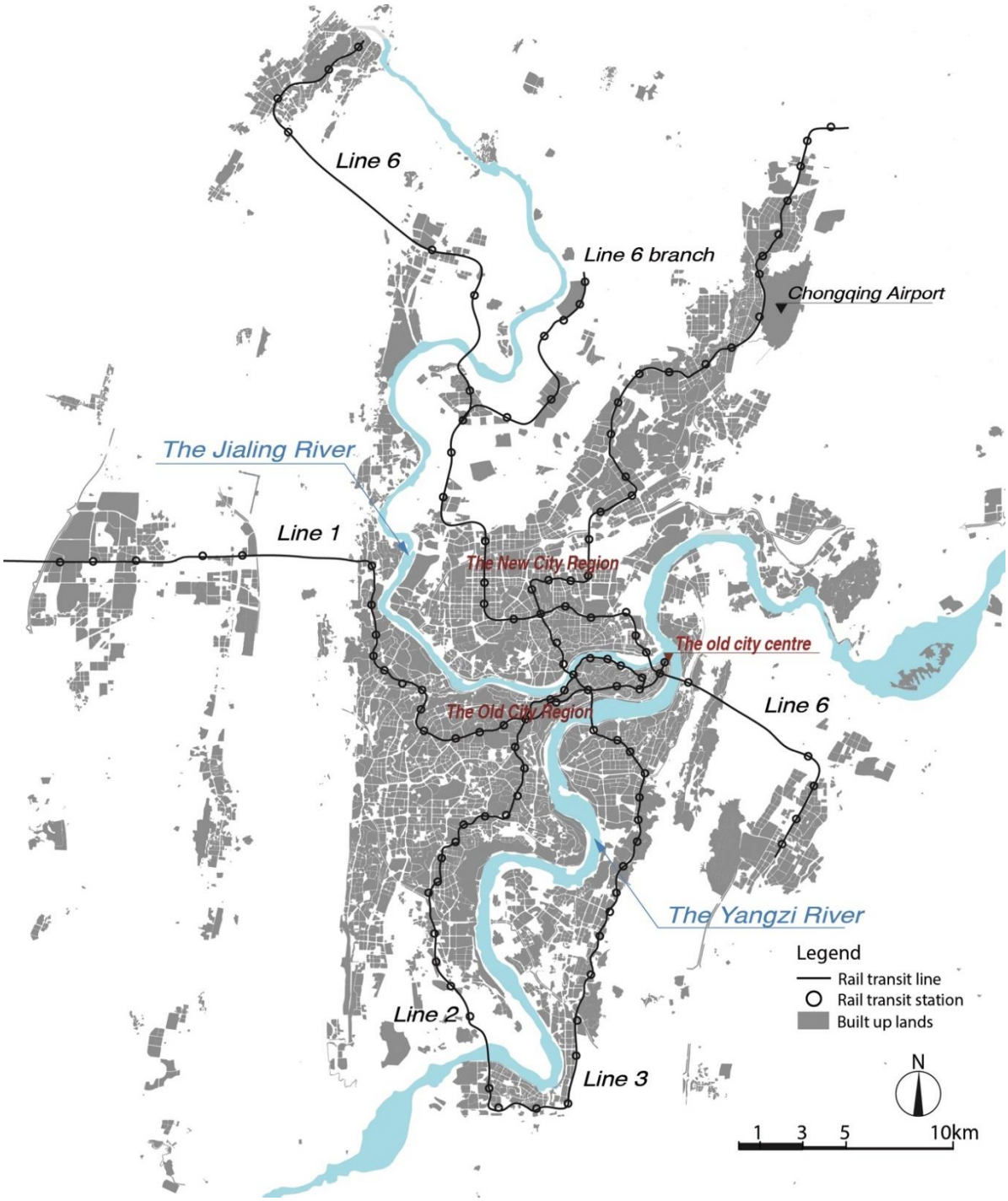

Figure 1: The central urban area of Chongqing (Author)

The association between people's travel-related variables and socio-economic characteristics and choice of rail transit for travel was modelled using data extracted from a citywide travel survey (Chongqing Urban Household Travel Survey, 2014), which took place three years into the operation of Lines 1, 3 and 6. Respondents were asked to report their commuting information on an ordinary weekday, which include home and destination locations, starting and arriving time, commuting mode choice. Their demographic characteristics, car ownership and living property type are also recorded. Data was

collected by staff with an electronic tablet equipped with specially designed GPS software to record people's location.

In the survey, the central urban area of Chongqing was divided into 25 transport zones. The sample size of each zone was based on its population size. The whole survey contained a sample of 80,000 persons, from 28,000 households and located in the main city region (representing a 1% sampling of the total population). Only part of the sample data was made available for research; data was extracted for analysis from zone 1 and zone 2, to represent almost the whole old city region; and zone 10 and zone 11, to represent the new city region. This yielded a dataset of 5,111 persons for comparison. Data from people below 18 years of age were excluded because daily trips of this group are almost always to school or travel with their parents. Trips of people above 18 are considered by destination (for calculating commuting distance) and mode choice. A final dataset amounting to 3,642 persons was used for the statistical analysis.

3.2 Variables and predictors

Table 1 displays the variable used as well as their definitions. The potential influential factors are selected as explanatory variables, including trip characteristics, built environment and socio-economic factors, drawing on previous literature (Ding et al. 2018, Golshani et al. 2018, Zhao et al. 2020). Commute distance and trip duration are included, as they show different elements of travel mode choice (Cervero 2007, Zhao 2013, Feng et al. 2013). Commute distance was calculated as the distance between the person's home and the destination of their outbound journey on an ordinary weekday, based on the road network in the city. Geographic accessibility to a transit station was calculated as the Euclidian distance from a resident's home to the nearest rail transit station. This is the only variable of the built environment, due to unavailability of other data sources. Socio-economic variables include age, gender, residential property type, car ownership, drawing on previous studies (Ohnmacht et al. 2009, Yu et al. 2019, Ao et al. 2020). Hukou status is also used to examine the difference in travel for the migrant population relative to the existing population. Residential property type is used to substitute people's income, since income data is not collected in the survey. Besides, income and car ownership are closely correlated, which implies that higher incomes make owning a car more feasible (Mackett and Sutcliffe 2003, Creemers et al. 2012).

Table 1: Variables and definitions

Variables	Description	Category	Mean/observations	S.E./percentage	Min	Max
Dependent Variable						
Transit mode choice	Travel mode chosen for the commuting trips	0=Other travel modes	3214	88%		
		1=Rail transit	428	12%		
Independent Variables						
Trip characteristics						
Commuting distance	The distance between the person's home and the destination, based on the road network in the city (km)		6.0	0.1	0.4	53.4
Trip duration	Time spent for the trip(min)		33.2	0.3	3	140
Built environment element						
Distance to the nearest transit station	Calculated as the Euclidian distance from a resident's home to the nearest rail transit station (m)		710.5	9.2	21.7	2758.2
Social economic attributes						
Age	Age of respondent(years)		41	0.2	19	89
Car Ownership	Household car ownership status	0=having no car	2519	69.2%		
		1=having at least one car	1123	30.8%		
Gender	Gender of respondents	0=Female	1827	50.2%		
		1=Male	1815	49.8%		
Hukou	Household registration status in Chongqing	0=Hukou holder	2653	72.8%		
		1=Non-Hukou holder	989	27.2%		
Property Type	Living property level	0=Old properties	807	22.2%		
		1=Ordinary or luxury property	2835	77.8%		

The distributions of the variable values are plotted spatially on the maps in Figure 2. The commuting distance in the new city region (to the north of the river) is generally much longer than in the old city region (to the south of the river) (Figure 2-a). Similar pattern is shown for the trip duration (Figure 2-b).

Car ownership is also higher in the new city (Figure 2-c), while a higher percentage of transit users accumulate in the old city region (Figure 2-d).

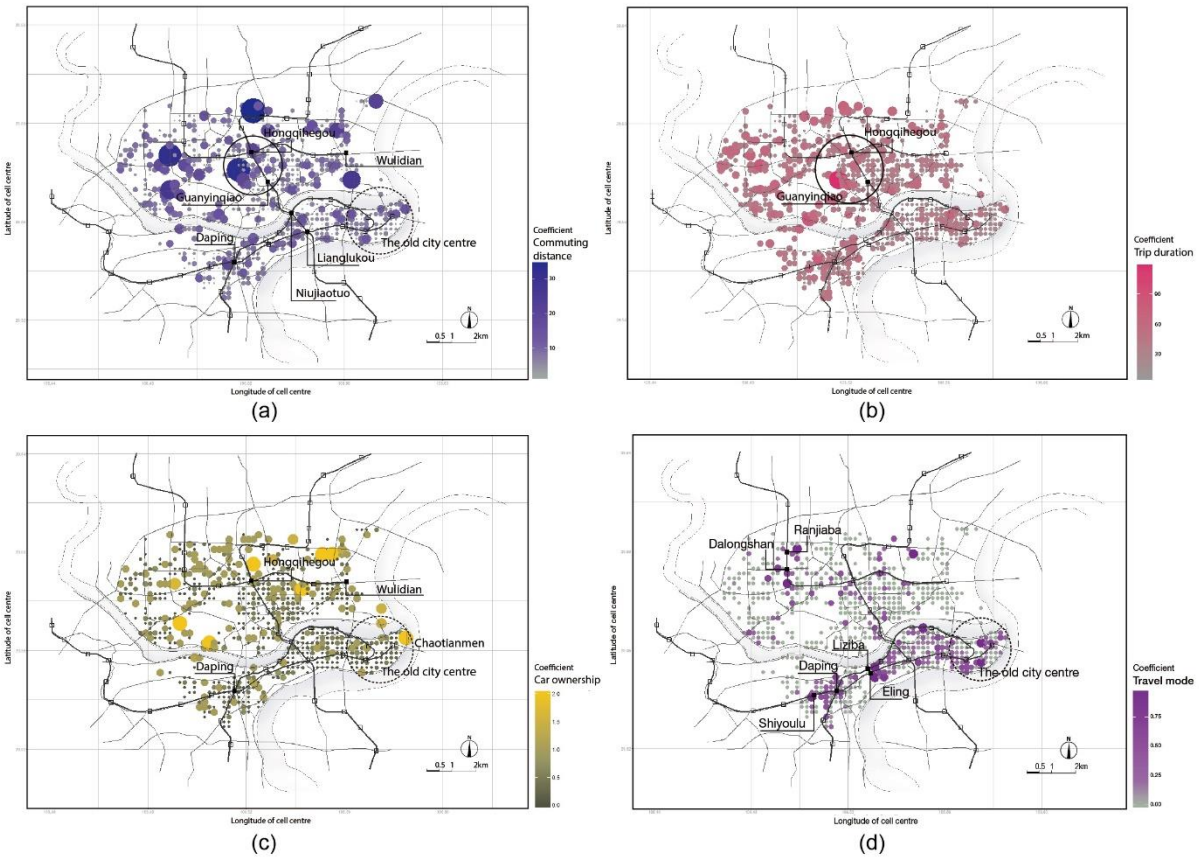

Figure 2: Descriptive analysis: (a) commuting distance (km). (b) trip duration (min). Higher saturation (of pink colour) and larger size of data-points indicates a longer trip duration. Higher saturation and larger size of data-points indicates a higher value. (c) car ownership (number of cars). (d) travel mode (1=rail transit, 0= other modes). (Author)

A cross-tabulation of commuting distance and travel modes in the city, by old and new city regions is shown in Table 2. Within both the old city and the new city, the longer the distance people travel, the higher the percentage of transit use. For example, the percentage of transit use in the old city is 8.3%, 26.3%, 31.3% and 33.3% for the commuting distances of 0–5 km, 5–10 km, 10–20 km and above 20 km, respectively. The largest increase in rail transit mode is between the categories of 0–5 km and 5–10 km (in the old city region), with the proportion increasing from 8.3% to 26.3%. A similar pattern is seen for the data from the new city. For example, 26.3% of people in the old city region who travelled 5–10 km chose rail transit as their travel mode, compared to only 8.5% of people who travelled in the same category of distance in the new city region. The data in Table 2 suggest that rail transit may have greater impact in the old city than the new city region (and may be facilitating people's longer trips),

and the GWR method is used to explore this spatial distribution in more detail.

Table 2: Percentage of transit use mode in different commuting distance categories grouped by region. Source: Citywide household panel travel survey 2014

		Rail transit		Other travel modes		Total	
Commuting distance categories		N	%	N	%	N	%
Old city region	0-5km	94	8.3%	1039	91.7%	1133	100%
	5-10km	142	26.3%	398	73.7%	540	100%
	10-20km	61	31.3%	134	68.7%	195	100%
	above 20km	22	33.3%	44	66.7%	66	100%
New city region	0-5km	31	3.3%	898	96.7%	929	100%
	5-10km	38	8.5%	410	91.5%	448	100%
	10-20km	26	11.0%	211	89.0%	237	100%
	above 20km	14	14.9%	80	85.1%	94	100%
Total		428	11.8%	3214	88.2%	3642	100%

3.3Modelling approach

This study examines the data first at the aggregate level by using a global logistic regression (GLR) model to explore which variables have an influence on transport choice. The strength and direction of association is indicated by the global regression coefficients. Moran' test is used to detect the spatial autocorrelation of the data and justify the necessity of GWR. A GWR model is then utilised to reveal the spatial variation in parameter estimates of the global model, as a reflection of what is unique about particular places. This follows previous studies (Yu 2007, Lu et al. 2014) in developing a global and spatially weighted model. The goodness of fit diagnostics of the two models are compared to identify the improvement of using the GWR method.

In logistic regression, instead of predicting the value of a variable Y, as in multiple linear regression, we predict the probability of Y occurring given known values of X_n. The logistic regression equation for the probability, P(Y), of Y occurring is given by:

$$P(Y) = \frac{1}{1 + e^{-(b_0 + b_1 X_{1i} + b_2 X_{2i} + \cdots + b_n X_{ni})}} \qquad (1)$$

The odds of an event occurring are defined as the probability of an event occurring divided by the

probability of that event not occurring. With one unit change in X_{ni},

$$\text{Odds ratio} = e^{b_n} \qquad (2)$$

In order to examine spatial heterogeneity, we need to employ local measures (Getis and Ord 1992, Anselin 1995). GWR can especially handle spatial heterogeneity by allowing the coefficients of a regression model to vary spatially and are commonly used in an exploratory fashion (Fotheringham et al. 2003). As the study aims to explore the spatial variation of each coefficient, the spatial varying patterns are useful for explanation. Therefore, GWR is adopted in this study. The GWR model is rewritten as:

$$y_i = \beta_0(u_i, v_i) + \sum_k \beta_k(u_i, v_i)x_{ik} + \varepsilon_i \qquad (3)$$

Where (u_i, v_i) denotes the coordinates of the i th point in space and $\beta_k(u_i, v_i)$ is a realization of the continuous function $\beta_k(u, v)$ at point i. GWR assumes that observed data near to location i have more of an influence in the estimation of $\beta_k(u_i, v_i)$ than data located farther from i. In order to estimate the parameters of the GWR model, Equation 4 can be expressed as a set of linear equations:

$$\mathbf{y} = (\boldsymbol{\beta} \otimes \mathbf{X})\boldsymbol{j} + \boldsymbol{\varepsilon} \qquad (4)$$

where $\otimes$ is the cross-product**,** and ***j*** is an all-ones vector of dimensions $(k + 1) \times 1$. The variables in bold type denote matrices:

$$\mathbf{y} = (y_1, y_2, \dots, y_n)^T$$
$$\mathbf{X} = \begin{bmatrix} 1 & x_{11} & x_{12} & \dots & x_{1k} \\ 1 & x_{21} & x_{22} & \dots & x_{2k} \\ & \dots & \dots & \dots & \\ 1 & x_{n1} & x_{n2} & \dots & x_{nk} \end{bmatrix} \qquad (5)$$
$$\boldsymbol{\varepsilon} = (\varepsilon_1, \varepsilon_2, \dots, \varepsilon_n)^T$$

Written in matrix form, the transpose of parameter matrix $\boldsymbol{\beta}$ in Equation 3 is estimated by:

$$\widehat{\boldsymbol{\beta}}(u_i, v_i) = (\mathbf{X}^T\mathbf{W}(u_i, v_i)\mathbf{X})^{-1}\mathbf{X}^T\mathbf{W}(u_i, v_i)\mathbf{y} \quad (6)$$

$\mathbf{W}(i)$ is an n by n spatial weighting matrix of the form:

$$\mathbf{W}(i) = \begin{bmatrix} w_{i1} & 0 & \dots & 0 \\ 0 & w_{i2} & \dots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \dots & w_{in} \end{bmatrix} \quad (7)$$

The weighting matrix $\mathbf{W}(\mathbf{i})$ in Equation 7 is a weighting scheme based on the proximity of the regression point i to the data points j around i. Where w_{ij}, as an element of $\mathbf{W}(i)$, is the weight given to data point j in the calibration of the model for location i.

In order to reduce problems when data in regions are distributed unevenly, this study adopts a spatially varying weighting method to calibrate the weighting matrix. It involves a bi-square weighting function which is related to the Nth nearest neighbours of point i. The weighting function determines the weight of each data point up to the Nth, and all data points beyond the Nth are set to zero. Therefore, the bandwidth is adaptive to include the same number of data points (N) at each regression point. The Akaike information criterion (AIC) is a measure of the relative quality of a statistical model for a given set of data. AIC provides a means for model selection. A corrected AIC (referred to as AIC_c) takes into account the different number of degrees of freedom in different models, so that their relative performances can be compared more accurately. A model with a lower AIC_c than another is held to be a better fit of the data.

4. Results

4.1 Global logistical regression model

A global model of logistic regression is utilised first to explore the impact of urban and social indicators on people's commuting choice of transit before GWR. The binary global logistic regression model (GLM1) of residents' transit mode choice is shown in Table 3. The goodness of fit of the binary logistical regression model was calculated using the Hosmer and Lemeshow goodness of fit (GOF) test in *R*

software, in which *P*-value = 0.0002424 (thus $p < .000$),demonstrating that this model was a good fit for the data. In this model, commuting distance, trip duration, distance to the nearest station, age and car ownership are found to be significant predictors of whether a person chooses rail transit as their main commuting mode. When commuting distance and trip duration increases, the probability of choosing transit as the commuting mode increases, with a reverse relationship for the remaining three. However, property type, gender and official residential status (Hukou) are found to be insignificant and are not discriminant factors in people's transit choice.

Table 3: Estimated binominal logistical model of transit mode choice (N =3642)

	Estimate	Std. Error	Z - value	Exp(B)
(Intercept)	0.054	0.272	0.201	1.056
Commuting distance	0.068***	0.009	7.866	1.070
Distance to the nearest transit station	-0.002***	0.000	-10.554	0.998
Age	-0.037***	0.005	-7.475	0.964
Trip duration	0.011***	0.003	3.448	1.011
Car Ownership	-1.077***	0.147	-7.326	0.340
Gender	-0.097	0.112	-0.866	0.907
Property Type	-0.038	0.129	-0.297	0.962
Hukou	0.059	0.122	0.487	1.061
Indicated by estimate with level of significance (* < 0.1, ** <0.05, *** < 0.01)				
Model fit:				
Null deviance: 2636.4 on 3641 degrees of freedom				
Residual deviance: 2213.3 on 3633 degrees of freedom				
AICc: 2231.3				
Pseudo R-square value: 0.1586457				
Hosmer and Lemeshow goodness of fit (GOF)： $\chi^2 = 34.068$, df= 8, $p < .000$				

The fourth column, Exp(B), in Table 3 is the exponential of b for the predictor, and is equal to the odds ratio (Equation 2). For example, the commuting distance data indicate that for every one kilometre increase in commuting distance, the odds of choosing transit increased 1.07 times ($e^{0.068} = 1.07$). In other words, an individual's probability of choosing rail transit divided by the probability of not choosing transit increased 1.07 times. The causality can be explained in two directions. One, if people travel longer distance, they are more willing to choose rail transit rather than other modes, such as buses or private cars; and two, by utilizing the newly built rail transit systems, people expand their commuting distance and thus change their travel destinations. There is likely to be a combination of these two factors, both of which suggest that the rail transit system facilitates people's longer distance commuting journeys.

With a 10-year increase in age, the factor would be raised to the power of 10, giving 0.693 (= 0.964^{10}), a considerable decrease in the odds of choosing rail transit. Therefore, in general, the older the person is, the less likely they are to choose rail transit. The odds ratio of choosing rail transit is 0.34 for car-owners compared to those with no access to a car. In other words, car owners are much less likely to choose rail transit as their commuting mode.

4.2 Examining spatial autocorrelation

A spatial autocorrelation test was conducted by using the statistic of Moran's I. Several kinds of spatial relationship can be used to construct the spatial weights matrix, which include weighting based on distance (e.g., inverse distance, fixed radius and *k* nearest neighbours) for point data. For this study, the *k* nearest neighbours is chosen for the point dataset. The reason is as follows. Firstly, the *k* nearest neighbours ensures that every observation has a specified number of neighbours. It is often applied when the density of observations varies widely across the study region, while inverse distance is commonly applied to continuous data. In this study, the density of the points (residential locations) is not uniform throughout space. Besides, it is likely that the amount of points nearby (population residing nearby) carry more weight than those points beyond. Defining the nearest number of points of radius is more appropriate than defining a distance, thus *k* nearest neighbours is adopted to find the significance of spatial autocorrelation.

Moran'I is then calculated with inverse distance weights of *k* nearest neighbours. The value of *k* needs to be identified. Taking a usual size of a residential community, for example with a population of around 1,000-2,000. It is supposed the population in the same community carrying more weights than outside. Therefore, taking the 1% sample in the survey, *k* is decided as 15. In order to compare spatial autocorrelation with different levels of nearest neighbours, the value of *k* was varied experimentally between 1 and 15. The result of the *k* nearest neighbour test is shown in Table 4. The first column of the table shows the value of *k* used for each iteration, and the second column shows the estimate of Moran's *I* statistic. The results are found to be significant, which means that spatial autocorrelation does exist in the data, but the estimated values of Moran's *I* are low. When *k* is 15, the estimated value of *I* is 0.076 and less than 0.1. It is still possible that some of the unexplained variance of the residuals in the global model result from applying a global model to a spatially non-stationary process. In order to model this

non-stationarity process better, GWR is used as a method to reveal the spatial variations (although they may be small) in relationships behind the global model.

Table 4: Moran's I statistics of residuals of binomial logistical regression for all the users

k	Estimate	P - value
1	0.181	4.59E-17
2	0.148	2.31E-22
3	0.115	2.05E-20
4	0.111	1.01E-24
5	0.101	1.95E-25
6	0.100	2.76E-29
7	0.091	1.98E-28
8	0.086	1.53E-28
9	0.084	1.89E-30
10	0.084	4.74E-33
11	0.083	2.19E-35
12	0.079	3.54E-35
13	0.078	2.48E-36
14	0.080	2.83E-41
15	0.076	1.33E-39

4.3Geographic weighted regression analysis

A general geographically weighted regression (GGWR) model was carried out in *R* software. GGWR can be used to deal with spatial variations in a logistic regression model. In order to eliminate the effect of the non-significant variables on the model effectiveness, only the significant variables are input into the GWR model. For comparison, a second logistical regression model (GLM2) is also carried out with only the significant variables. Bandwidth, R-squared and AICc results for GLM 2 and GWR are given in Table 5. As explained previously, a model with a lower AICc is held to be a better fit of the data.

As expected, the GWR models provide better model fit diagnostics than the global regression does. R-squared values has been increased by around 94%, and AICc has been reduced by almost 115. However, the R-squared value is still relatively low, explaining 31% of the variance of the model. This is because the reason for choosing transit as commuting mode is more complicated than the explanatory variables included in the model. However there is still a significant level of explanatory power in the model.

Table 5: Calibrations and outputs for the model via and logistical regression and GWR

	GLM2	GWR
Bandwidth	-	363
Pseudo R-square	0.16	0.31
AICc	2226.41	2111.70

Table 6 is a summary of the coefficient estimates of GLM2 and GWR. The global regression gives a stationary coefficient estimate of the variables. Local coefficient estimates are mapped to investigate for any change in data relationship across space (Figure 3-Figure 7).

Table 6: Summaries for the coefficient estimates of Logistical regression and GWR. Logistical regression gives a stationary coefficient estimate.

	GLM2 coefficient estimates	GWR coefficient estimates				
	stationary	Min.	1st Qu.	Median	3rd Qu.	Max.
(Intercept)	0.041	-3.873	-1.172	-0.117	0.965	3.734
Commuting distance	0.067***	-0.053	0.040	0.077	0.115	0.298
Distance to station	-0.002***	-0.009	-0.003	-0.003	-0.002	0.003
Age	-0.038***	-0.109	-0.056	-0.041	-0.020	0.013
Trip duration	0.011	-0.042	0.004	0.015	0.027	0.051
Car ownership	-1.089***	-3.608	-1.606	-1.047	-0.610	0.666

From the coefficient maps of commuting distance and trip duration, variations of the coefficient patterns emerge across different areas. The contributions of commuting distance (Figure 3) and trip duration (Figure 4) to the choice of rail transit mode are both the most significant in the old city centre and its adjacent area (dashed circle with grid units of brightest yellow colour). It means people in the old city centre benefit from the service the transit provides for both long distance and long duration trips. It is evident that the effect of rail transit development is the most significant in facilitating people's travel there. However, the patterns of the two coefficients are exhibited in contrast around the nodes of the two lines in the northern new city region (solid black circle in Figure 3 and Figure 4), with the highest positive coefficient for the former and the lowest negative for the latter. It means if distance is longer or time is shorter, people in the new city area more likely to choose rail transit. It suggests people have more concerns on the efficiency the rail transit provides. However, when travel time extends, people are least likely to choose transit and may be attracted by other modes, such as private cars (higher car ownership shown in Figure 2). The lowest level of coefficient of commuting distance is exhibited at Daping; where commuting distance changes there is little impact on the probability of choosing transit.

It means the long-distance travel ridership can shift to alternative travel mode choices, as there is convenient bus service there.

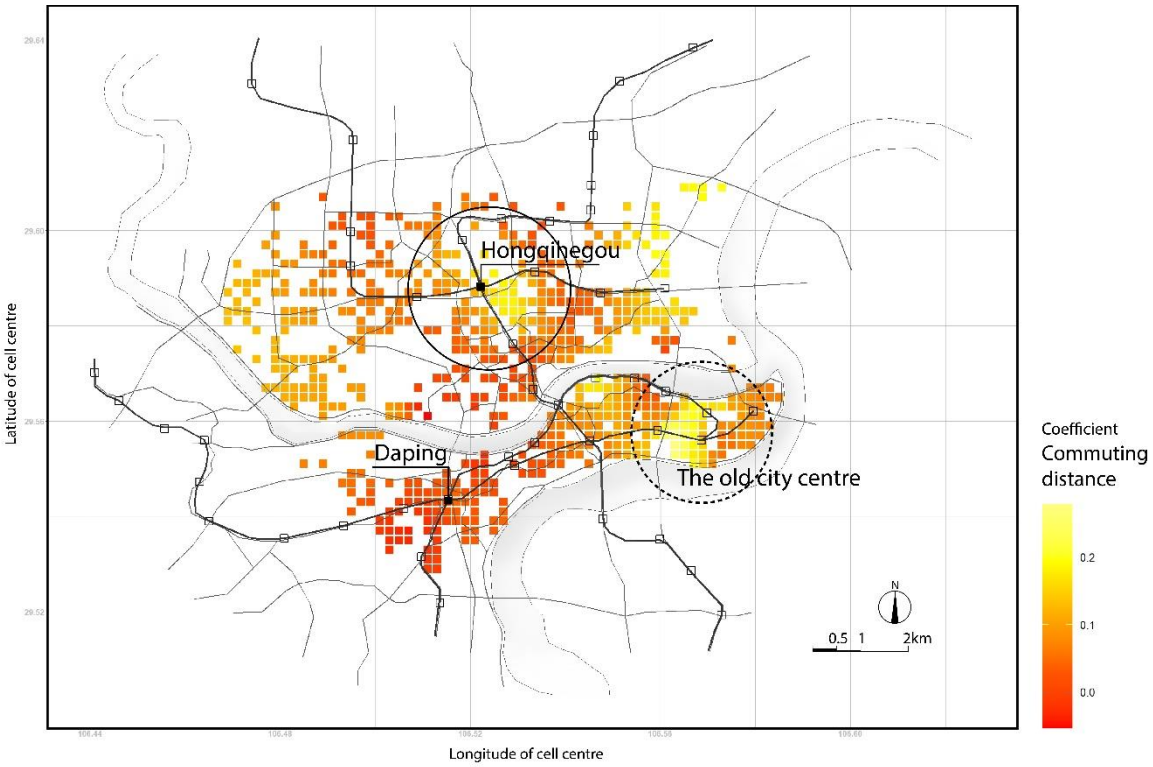

Figure 3: Coefficient (Estimate in Table 3) of the independent variable *commuting distance* in predicting choice of rail transit as mode of travel. The coefficient represents the change of logit of the outcome variable (travel mode choice) associated with a 1 km change in commuting distance. Bright yellow indicates a higher (more positive) value of coefficient than dark red. (Author)

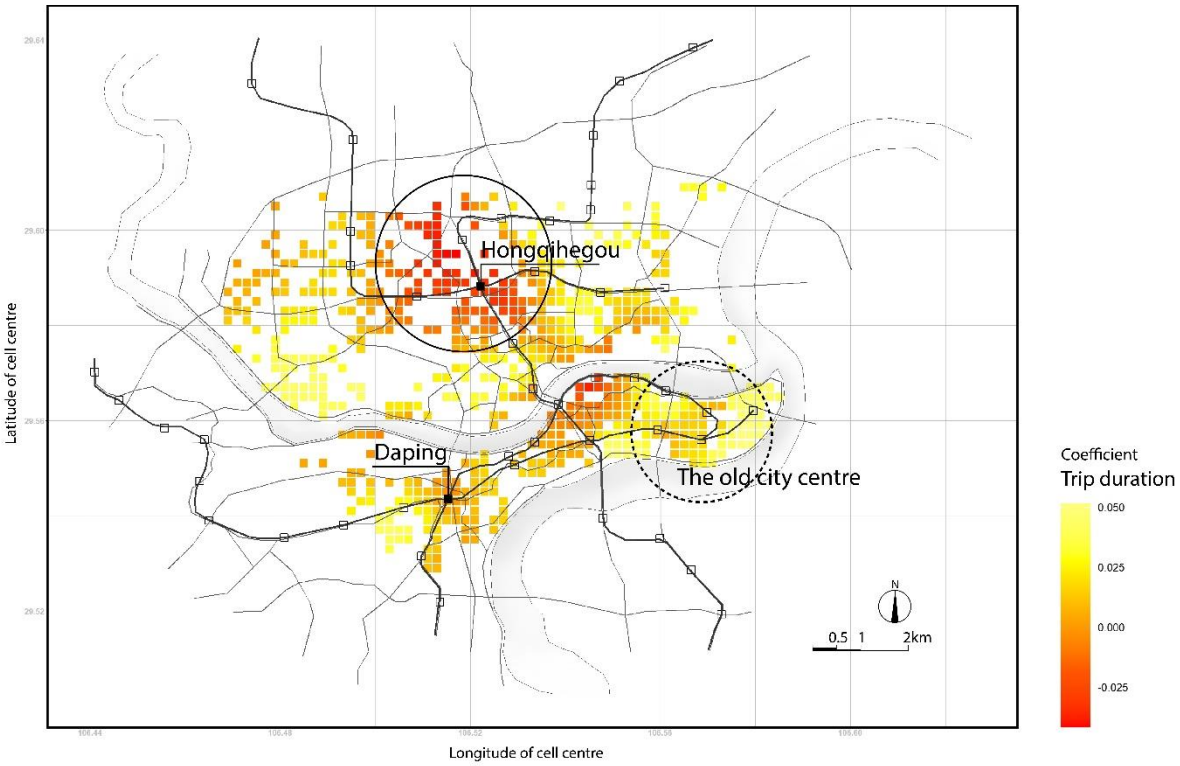

Figure 4: Coefficient of the independent variable trip duration in predicting choice of rail transit as mode of travel. The coefficient represents the change of logit of the outcome variable (travel mode choice) associated with a 1 min change in travel time. Bright yellow indicates a higher (more positive) value of coefficient than dark red. (Author)

The old city centre is the political and financial centre of Chongqing, while there are still many established residents. Most of the established residents work at the adjacent area in the peninsula and walk daily to their working place. However, the employment opportunities for the established residents are limited in the old city centre, which are mostly either office jobs requiring high skills, or service jobs which they are not willing to take. There are also very limited choices for travel mode, and the bus provision is not convenient due to the road structure in the mountain topography, which is specific to the layout of Chongqing. People often have to walk a long distance either up or down steep slopes in order to get to the nearest bus station, and this is even more of a problem when getting to a rail transit station. As shown in Table 2, in the old city region there is a dramatic increase in rail transit mode from the category of 0–5 km to 5–10 km, with the proportion increasing from 8.3% to 26.3%. The 5-10km commuting distance is outside the peninsula. If commuting distance increases, it is likely that the travel destination is changed to outside the peninsula and this makes transit more likely.

The inconvenient public transport service in the old city centre also explains for the discrepancy of

coefficient ‘household car ownership’, as presented in Figure 5. This variable’s contribution to the choice of rail transit is the most negative in the old city centre (dashed circle in Figure 5). This suggests that car ownership makes the person less likely to choose rail transit as their commute mode. Conversely, people who do not own a car are much more likely to use rail transit in this area. In comparison, owning a car in other parts of the city is not as decisive in people’s choice of transit as in the old city centre. This analysis provides different results from much of the western literature. For example, for the JLE extension, the established residents, who are less likely to be car owners, enjoyed limited benefit from the new metro investment either in transit use frequency or commuting distance expansion (Lane et al. 2004).

As the literature has indicated while choosing higher pay jobs and higher quality goods often requires a longer distance commute, established residents were more likely to have a lengthier travel time and cost (Zhao and Li 2019). In this case, without the rapid public transport system, the established residents who don’t own a car were especially lacking options to expand their travel destinations. The result of the distinct patterns of coefficients in the old city centre indicate that the rail transit supply works as a leverage for the socially disadvantaged population to access jobs and opportunities, and thus to some extent alleviates the transport-related social inequity.

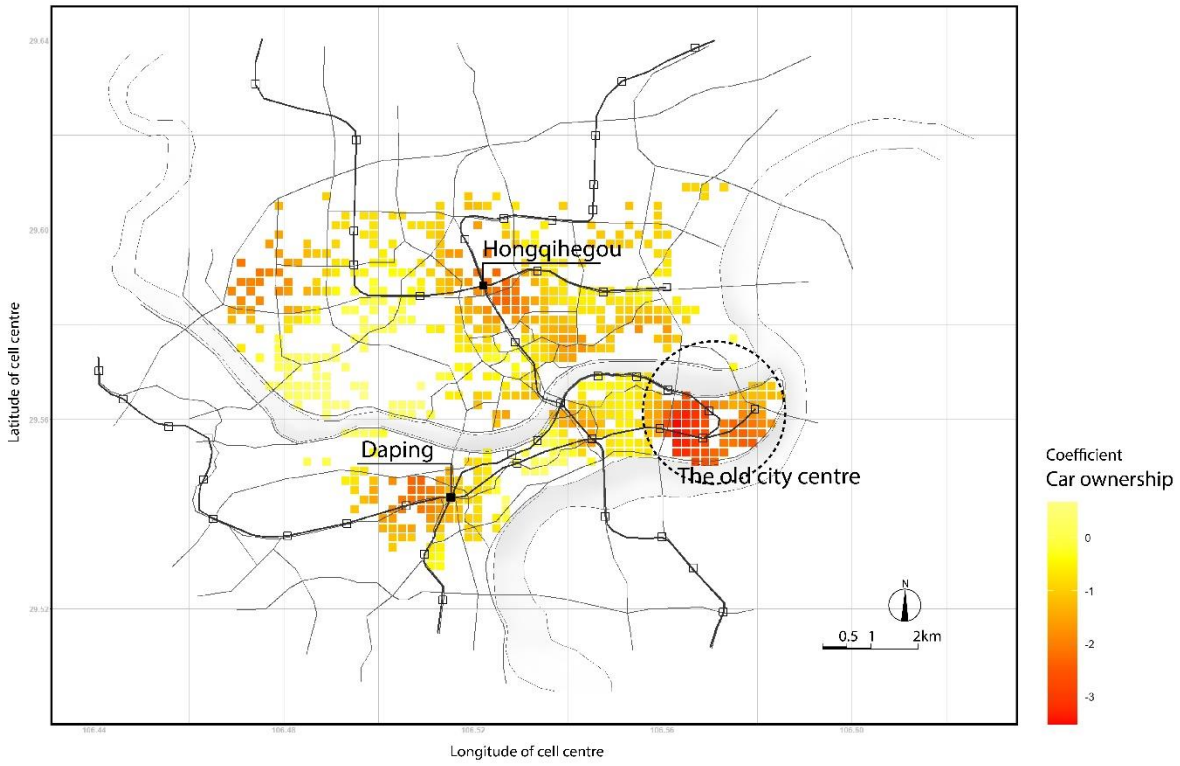

Figure 5: Coefficient of the independent variable car ownership in predicting choice of rail transit as mode of travel. Presented as per Figure 3, but for a one unit change in the categorical variable 'car ownership'. Values are negative, with bright yellow indicating a value closer to zero, and dark red indicating the most negative values. (Author)

Meanwhile, the lowest level of coefficients for 'age' and 'distance to the closest transit station' both emerge in the transit-sparse areas of the new city region, which respectively exhibits as the red colour along the southwest bank for the former and accumulates in the east side for the latter. The disparities of coefficient patterns reflect how the specific spatial context has an influence on the transit mode choice and is attributed to social inequities.

The proximity to transit station is the most negative in the east side of the new city region (dashed black circle in Figure 6). This area has been newly regenerated with some high-level residential properties and is close to the area of the new financial district of the city. If people live further from the rail transit station, it is the least likely that they would take the rail transit for their daily commuting trips. In comparison, the value of coefficient is next to zero at the old city, where the influence of distance from the station can be neglected. One possible reason is that peoples' travel choice of transit is shaped by other factors alongside the factors relate to transit. High density and mixed land use around the transit stations in the old city includes public services and retail, which provides further attraction for people

to choose transit. Besides, the higher density of transit network in the old city also provides multiple choices of nearby transit stations, similar to findings elsewhere (Zhao and Li 2019). At Wulidian, there is a low level of mixed land use with gated residential communities, large block size and wide streets, and in 2017, only one rail transit station nearby. When the distance to transit station increases, people resort to other travel modes, such as the car or bus.

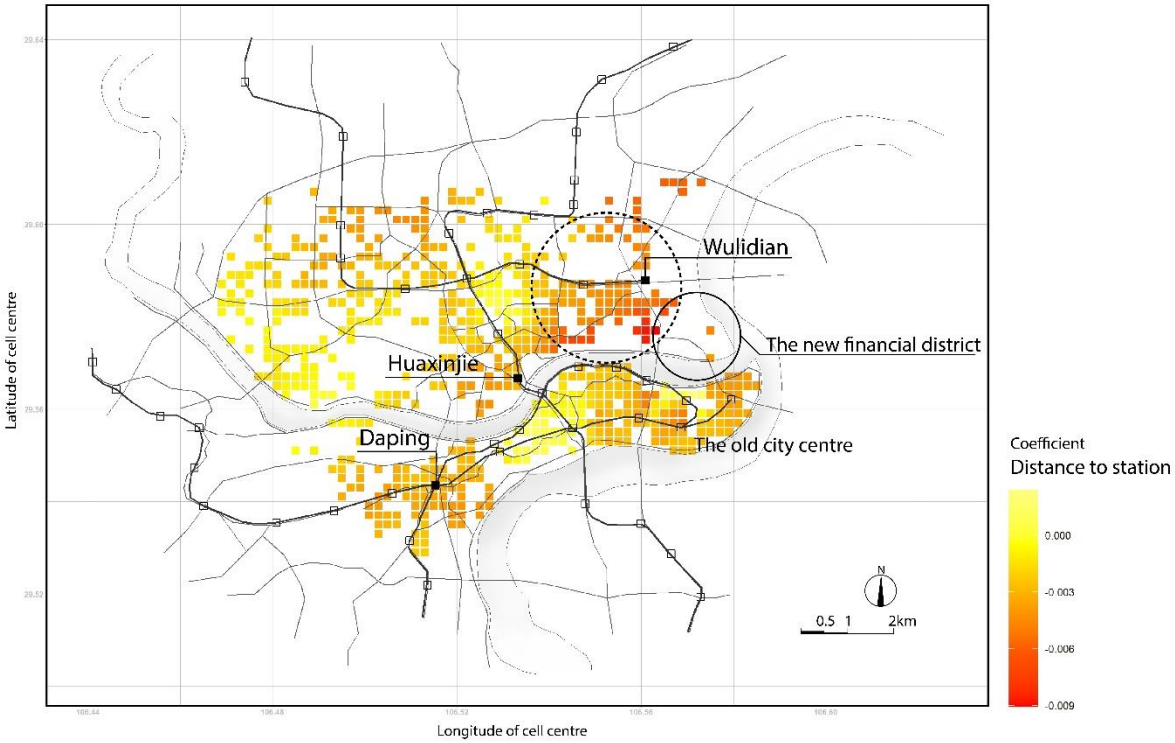

Figure 6: Coefficient of the independent variable *distance to nearest transit station* in predicting rail transit as choice of mode of travel. Presented as per Figure 3, but for 1 metre change in distance to nearest transit station. Values are negative, with bright yellow indicating a value closer to zero, and dark red indicating the most negative values.

A highly negative coefficient of 'age' in certain areas may indicate an exclusion of the older generation from equally receiving the benefit of rail transit investment (Figure 7). The pattern in the new city region shows a distinctive division. In the new city region, the topography is quite flat. The northeast part of the new city region (dashed circle in Figure 7) has a coefficient pattern close to zero. It means in this area there is almost no difference of transit use with age. It has a density of rail transit network coverage that is comparatively high for the rest of new city region. The 'age' variable's contribution to the choice of rail transit is the most negative at the southwest bank of the new city region along the Yangzi River (the red belt in the map). Figure 7 shows that this region is transit sparse and has a very limited access to nearby rail transit stations. Meanwhile, the whole old city region (the peninsula) has a similarly low

level of the age coefficient compared to the new city region. The difference could again be ascribed to the mountain topography of the old city, especially near the river bank, which may make it more difficult for elderly people to access the station.

Therefore, accessibility to the transit station, which covers both distance and steep topology to the stations, has the potential to exclude elderly people from use of the rail transit in some areas. In a comparatively flat topography, a denser transit network can facilitate the elderly's use of transit. However, in the steep topography, complimentary planning interventions are required alongside the transit development to overcome the lack of mobility in some groups, perhaps using some form of bus feeder connections into the main public transit system.

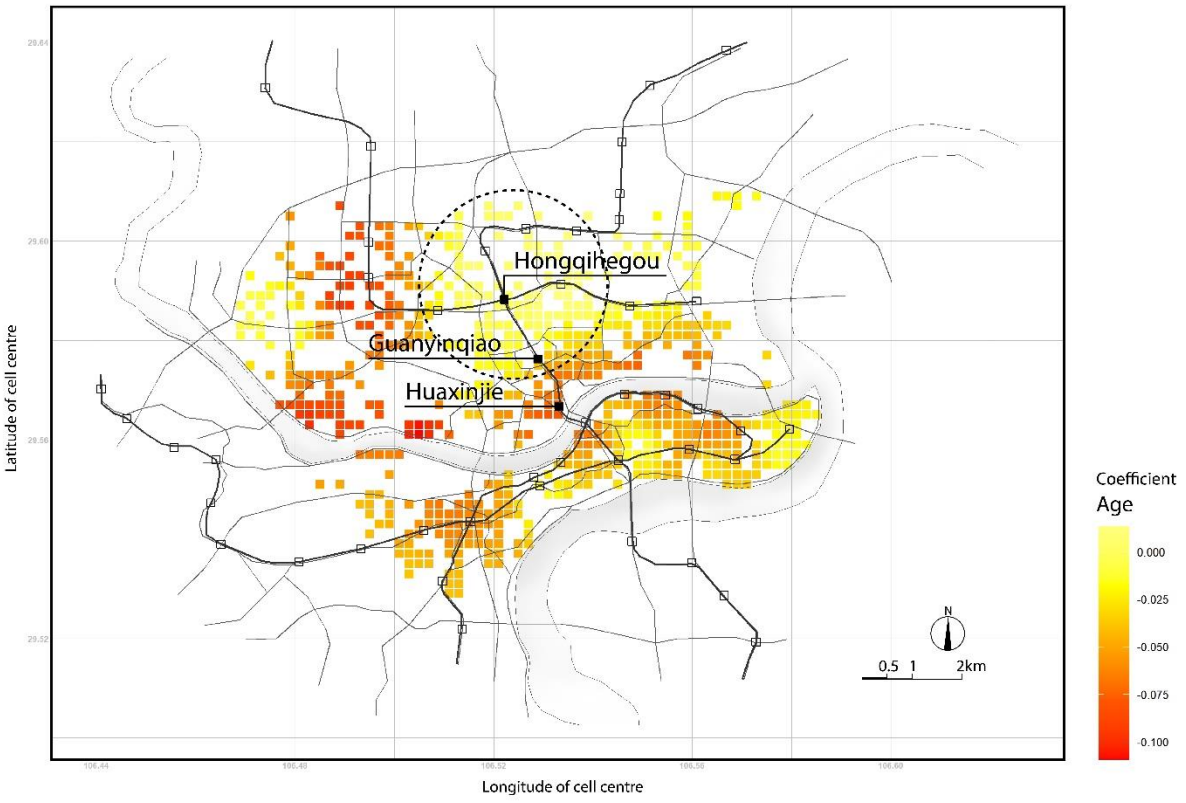

Figure 7: Coefficient of the independent variable age in predicting choice of rail transit as mode of travel. Presented as per Figure 3, but for a 1- year change in age. Values are negative, with bright yellow indicating a value closer to zero, and dark red indicating the most negative values. (Author)

5. Conclusions

Access to public transit varies over space, in quite subtle ways, relative to the extent of the transit network and the physical and built form context. This paper explores the spatial variation of the

influential factors on people's transit mode choice in Chongqing, finding that transport access differs significantly across space. As Banister (2018) mentions, there can be a 'double equity' impact in terms of transit access, whereby new infrastructure can be positive for higher income groups and negative for lower income ones. This is also unevenly spatially distributed. The analysis identifies the role that rail transit plays in mitigating inequity in transport access, especially in the transport disadvantaged areas of the city. This contributes to a more in-depth understanding of the socio-spatial distribution of benefits of new transit development, which closely relates to people's attributes associated with mobility disadvantages, such as age.

Three main conclusions are drawn. First, the role of rail transit systems is important in mitigating the inequity of transit access especially in the more deprived, old city areas. The results of the global regression model are generally consistent with previous studies (Cervero 2007, Ohnmacht et al. 2009, Zhao 2013), with commuting distance, trip duration, home proximity to transit station, car ownership and age all significant to transit choice. The results of the GWR model give a more in-depth understanding. Different patterns are exhibited across the city, especially between the old city and new city region, and even more distinctive between the old city centre and the rest of the whole city. For example, rail transit is the most effective in facilitating travel when commuting distance and trip duration increase and for those without a car in the old city centre. Considering the social characteristics of residents in the old city centre, there are a number of neighbourhoods where a high level of established residents and rural migrants (with relatively low incomes) are concentrated, without access to private cars and also with limited access to other public transport facilities. The use of accessibility interacts with their socio-economic conditions, in this case, there are limited employment opportunities for their employment skills in the old city centre. The rail transit system plays a more important role in benefiting the travel of established residents in the communities which haven't experienced dynamic changes through redevelopment and helps expand their job possibilities. Transport investment can be used in this way to benefit certain population groups or spatial areas (van Wee 2012, Lucas et al. 2016), but often this spatial dimension of transit investment is overlooked. For example, a denser transit system could be deliberately applied to the old city centre and other established areas with poor public transit access, with new lines across these areas linking to new employment opportunities.

Second, in order to have greater impact on people's choice of transit, the development of the rail transit should be completed with mixed use development around and good accessibility to the station. The routes to the rail transit stations require a walkable environment to get to the station and mixed land use around the station to help people's choice of transit. A dense transit network with multiple nearby stations promotes usage. There are related implications by resident age. The most negative pattern of age appears in the transit sparse areas as the low level of accessibility has prevented the elderly group from use of transit. To solve this problem, last-mile connectivity with feeder buses or other modes are especially important for elderly people to get to the transit station. This should be implemented generally in the old city and also along the south bank of the new city. As the development plan of the government intends, every individual in China deserves equitable access to urban public transport services, especially for those with spatial and mobility disadvantages (MoT. 2011).

Third, the role of transit in promoting equitable travel for different population cohorts is important. In this research, gender, property type, Hukou are not significant variables for people's choice of transit. This is inconsistent with other research findings, that there are different 'winners' and 'losers' according to their Hukou or economic status from the regeneration effect of metro investment (Zhao and Howden-Chapman 2010, Jones 2015). The reason can be explained by the low fare for transit and subsidy by the government in Chongqing – this is critical for access to transit. By 2021, compared to other megapolises with a population of more than 10 million, Chongqing has a lower ticket fare for even relatively long journey distances. A fare of two yuan lasts for journeys of 6 kilometres, compared to the bus tickets of one or two yuan. However, Shanghai and Beijing have a starting fare of three yuan and Guangzhou and Shenzhen two yuan for only 4 kilometres, a steeper fare increase than Chongqing. The cost of transit is also very different to a western context, such as London or a North American city. Besides the lower ticket fare, a policy is also used for no additional charge for transfer from transit to bus within half an hour. Public transit is viewed as a public investment; beyond the capital investment, there is a governmental operational subsidy of 6.2 billion for the rail transit system from 2007 till 2019. The ticket fare compensates for less than 70% of the annual operational cost, and the rest is covered by subsidy (ChongqingDaily 2020). The fare policies have assisted in usage of public transit for low income groups and rural migrants, whereas elsewhere they may have difficulties in accessing employment opportunities and other activities due to the cost of public transit.

There are some limitations with the approach used in the analysis. Only the data from the central city could be accessed and analysed in this study. Future research could include wider data to represent the spatial patterns of rail transit across the city. Besides, the categories of data gathered in the citywide travel survey dataset were limited due to data availability. For example, built environment elements are not available, such as density, diversity, etc. Future research can include more variables relating to the built environment, which are all potential characteristics influencing travel mode choice and may promote model prediction levels. In terms of empirical method, classical GWR assumes that all of the processes being modelled operate at the same spatial scale by determining an optimal bandwidth. A further version of GWR, multiscale geographically weighted regression (MGWR) allows different processes to operate at different spatial scales (Fotheringham et al. 2017), providing valuable information on the scale at which different processes operate. MGWR is hence a useful future approach to examine the spatial non-stationarity relationships.

The research in this paper provides important quantitative evidence for planners to understand spatial differences and develop strategies to meet the needs of different groups when seeking to achieve a more equal distribution of the benefits of transit investment. Though the study case has topographical constraints of the city (particularly in the old city), conclusions can be generated for developing planning strategies. Planning transit lines to the established areas with inconvenient public transport access are most important. It is in these areas that the socially disadvantaged groups are more likely to travel locally. Rail transit provision can have greater impact in promoting transport-related social equity for those expanding their trips. Providing last-mile connectivity with bus services to the steep areas in the old city and river bank and an improved walkable and elderly-friendly neighbourhood design that enhances accessibility to the transit stations is critical. Good accessibility to transport facilities, a supportive surrounding neighbourhood design and travel with comfort can meet with the elderly's mobility needs. Promoting mixed development by planning for more services and retail near the transit stations can also support transit usage. Finally, and overlooked in many contexts, transit fare subsidies are also needed, especially for lower income groups and migrants to expand their travel possibilities for jobs and wider activities. Investment in urban transit is expensive and needs to be thoroughly studied to ensure impacts are as expected, and particularly the distributional issues can be quite complex. A harmonious society

requires equitable access to activities, and an important part of this requires equitable access to and use of the transit system.

(8192 words plus references)

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