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Identification and Mechanism of Residents' Regional Non-Commuting Flow Patterns Based on the Gradient Boosting Decision Tree Model: A Case Study of the Shanghai Metropolitan Area

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Abstract: With the improvement in residents' living standards, non-commuting has gradually become an important daily transportation behaviour for residents. The intensity of non-commuting flow can reflect the level of urban functional services and external attractiveness and can intuitively characterise the interconnection pattern and relationship among various cities within the metropolitan area. Related research is also a key topic in the fields of urban planning and transportation geography from a humanistic perspective. Taking the Shanghai Metropolitan Area as an example, this study explored the characteristics of the non-commuting flow of residents in the region and between cities and its nonlinear influencing factors with the help of the mobile phone signalling data and the gradient lifting decision tree model. Three conclusions were identified: first, non-commuting flow within each city in the metropolitan area was concentrated in the central urban area, while non-commuting flow between cities was concentrated in the central urban area of the urban border and strong core cities. Second, the built environment had a nonlinear impact on residents' non-commuting flow. Different types of large-scale service facilities had different impact mechanisms on non-commuting flow, and public service facilities and transportation infrastructure jointly affected residents' non-commuting flow. Third, transportation facilities had a more significant impact on the non-commuting flow between cities. Large tourism, cultural, and medical service facilities had a more significant impact on non-commuting flow within cities, with upper or lower thresholds according to the type of facility. The planning strategy needs to conduct targeted planning, regulation, and facility configuration based on the area's actual needs. In addition, this study identified the characteristics of non-commuter flow differentiation in street towns and the nonlinear impact of the built environment.

Keywords: non-commuting flow; nonlinear effects; gradient elevation decision tree model; Shanghai metropolitan area

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1. Introduction

With the continuous deepening of urban and regional connections, non-commuting flow by residents has gradually become an important element in the organisation and evolution of urban and regional space. Its characteristic patterns and impact mechanisms have gradually become the focus of attention in fields such as geography and urban planning. Non-commuting flow is a branch of the resident travel system, which includes short-term travel behaviours such as shopping and leisure. This type of behaviour helps to improve the quality of life of residents and expand urban functions [1]. Previous studies have classified residents' travel behaviour into three categories: maintenance activities, leisure activities, and essential activities [2]. The first two categories belong to non-commuting

flow, and the last category belongs to commuting travel. Compared to commuting, the non-commuting flow has high elasticity and strong randomness. Traditional commuting travel models often focus on commuting behaviour as the research object, whereas the analysis and prediction of non-commuting flow have limitations [3,4]. Previous studies have mostly focused on behaviours such as leisure tourism during holidays [5,6]. Scholars have conducted research on residents' travel behaviour based on travel survey data in Guangzhou and found that residents' non-commuting behaviour on rest days is significantly higher than that on working days. Although the distance difference between these two modes of travel is not significant, the non-commuting time on rest days is significantly longer [7].

Some scholars have also analysed the data of bus card swiping in Beijing and found that non-commuting flow is mostly concentrated in traditional scenic spots and the surrounding areas of large commercial centres. Non-commuting behaviour has formed multiple clusters centred around these areas [8]. Overall, some studies have explored the characteristics of daily non-commuting flow [9]. However, quantitative analysis of non-commuting flow at the regional level is relatively scarce. Japanese scholars have quantified the commuting characteristics of female workers in metropolitan areas and reviewed existing research on transportation connections among countries at a regional scale [10]. There is little research focusing on daily non-commuting flow behaviour at the regional level. In addition, existing research has focused primarily on commuting within cities, with some in-depth exploration of the mechanism of non-commuting flow among residents at the regional level, lacking theoretical support for urban agglomeration scale facility planning and resident travel guidance [11]. Among many forms of regional spatial organisation, the metropolitan area, as the final form of regional urban organisation division of labour, is conducive to the circulation of elements and functional connections between cities [12,13]. Therefore, at the level of urban agglomeration, starting from the regional and urban levels, it is conducive to in-depth analysis of the spatiotemporal characteristics and main influencing factors of residents' non-commuting flow.

According to the theory of time geography, travel behaviour is comprehensively affected by multi-dimensional factors such as residents' attributes, behavioural ability differences, and external objective environment [12]. Among many influencing factors, such as personal subjective preferences, social and interpersonal relationships, and the built environment, the built environment is considered an important factor influencing residents' travel behaviour [9]. Some studies also show that administrative boundaries have a strong impact on residents' travel patterns [13], and there are significant differences in the impact of built environment organisational structures of different scales on the non-commuting flow [14]. Previous studies have confirmed that factors such as public transportation accessibility, public service facility mix, and destination accessibility can significantly affect travel behaviour [15–19]. Furthermore, some studies have also explored the travel characteristics and impact mechanisms of temporary resident populations between cities [20,21]. The temporary resident population refers to those who have lived in one city for no more than six months [21]. Research has found that resource factors such as public service levels, characteristic tourist attractions, and large commercial centres can increase the frequency of residents travelling between cities. In contrast, urban economic aggregates and residents' disposable income have an inhibitory effect on intercity travel. Overall, existing studies have focused mainly on commuting behaviour, lacking systematic research on the influencing factors and mechanisms of non-commuting behaviour.

Machine learning methods extract association feature patterns from known sample training sets through regular analysis and then extract association datasets from unknown datasets [22,23]. In recent years, machine learning algorithms have been widely applied in neighbouring areas such as pattern recognition, and this method has significant practical application value in identifying residents' travel behaviour patterns. It is worth noting that existing studies usually regard the impact of the built environment and other factors on residents' travel behaviour as a generalised linear relationship and then select mathematical-

statistical models such as linear regression [24] and geographically weighted regression [25] for parameter fitting. However, some studies have also identified nonlinear mechanisms, such as threshold effects in relevant action models through machine learning methods. This mechanism exhibits significant threshold characteristics, where the model exhibits both linear and nonlinear correlation relationships [26–28]. The switching of this relationship depends on the stage conditions under which the model factors are located. In research branches such as transportation means [29], average daily passenger flow at bus stops [22], and average daily travel volume [30], studies have begun to explore the nonlinear impact mechanism of the built environment on commuter travel of residents, thus revealing the complex interaction between the built environment and residents' travel behaviour [31]. Some scholars believe that within a certain threshold, building density is too high, building spacing is too large, and high-rise buildings in the block can reduce the living experience, thereby increasing the psychological pressure on residents to commute and hindering their commuting [31].

Commuting behaviour refers to the transportation behaviour of residents between the enterprise and their place of residence. It represents the residents' work needs and is a necessary transportation behaviour with fixed routes. Non-commuting behaviour reflects the residents' daily life and leisure transportation connections between cities, with strong subjective willingness. Non-commuting travel is an important component of urban residents' travel, and its travel time and destination are more flexible [32]. The strength of non-commuting connections between cities can fully reflect the attractiveness of the core cities' public service facilities to surrounding residents. The spatiotemporal characteristics of non-commuting flow can reflect the central cities' attractiveness and influence in the region [33]. There are two main types of international research on non-commuting flow; the first type focuses on the main factors that affect residents' non-commuting flows within cities. The second type analyses the spatiotemporal characteristics of non-commuting flows at the regional level [34,35]. Specifically, various influencing factors such as regional spatial patterns, urban built-up environment, personal socio-economic attributes, and family characteristics have a significant impact on non-commuting travel [36]. In terms of regional spatial patterns, scholars have studied the impact of multi-canter city morphology on residents' different transportation modes and non-commuting frequencies [37]. In terms of the built environment, some scholars have explored the impact of public service facilities and transportation environments around residential areas on non-commuting travel preferences and decisions [38,39]. In terms of personal attributes and family structure, studies have shown that factors such as age, gender, and the number of family cars are significantly correlated with non-commuting travel distance and travel patterns [40]. Based on the characteristics of non-commuting travel within the region, researchers can effectively analyse the supply–demand relationship between urban facility layout and the residents' actual needs [41]. We classify different types of transportation behaviours and correspond to the types, levels, and scales of facilities required by different types of people, which helps to optimise the layout and functional improvement in regional public service facilities.

Due to the limitations of traditional traffic survey methods, it is difficult to accurately identify residents' travel trajectories [42]. With the development of big data technologies such as GPS satellite positioning data and mobile signalling data, the academic community has established a relatively complete method system for identifying workplaces, residences, and commuting using traffic trajectory data [43]. Therefore, based on the spatiotemporal patterns and activity types of traffic behaviour, combined with land use attributes, station distribution, and travel modes, traffic data can be applied to identify various travel modes, to analyse the dynamics spatiotemporal characteristics of residents' different travel activities [44,45]. With the support of multi-source transportation big data fusion technology, research has constructed identification methods for non-commuting activities and identified key parameters and thresholds for different travel purposes and modes [46]. This method compensates for the shortcomings of traditional research methods, such as small sample size and difficulty with questionnaire data and provides theoretical and

methodological support for the identification of other non-commuting traffic activities. Existing research has expanded the recognition technology of non-commuting travel patterns [47,48]. On the one hand, based on transportation travel chain data mining, the recognition method system and theoretical framework for non-commuting travel activities have been constructed [49]. On the other hand, the study identified the spatial pattern of regional non-commuting behaviour and applied it to the comprehensive evaluation of public service accessibility and spatial fairness, providing more effective suggestions for guiding the layout of public service facilities [39]. In summary, current research on the characteristics and influencing factors of residents' travel mainly focuses on commuting modes within cities [13,17,21]. Scholars have paid insufficient attention to non-commuting flow at the regional level and have not examined the nonlinear influencing factors of non-commuting flow behaviour [22,31]. Only a small portion of research focuses on non-commuting flow in the region, such as short-term travel tends to occur within the same administrative region, with a lower frequency of cross-regional travel [22]. Based on multi-source data such as point of interest (POI) and mobile signalling, this study used social network analysis, gradient boosting decision tree (GBDT) model, and other methods to identify the characteristics of the non-commuting flow of residents in the Shanghai metropolitan area. On this basis, this study explores the nonlinear relationship between residents' non-commuting flow and built environment elements, such as public service facilities and transportation facilities in the metropolitan area. This study identifies the differences in non-commuting flow habits of different types of people in the metropolitan area and supplements the research results of the nonlinear relationship between non-commuting flow and built environment elements.

2. Data and Methods

2.1. Research Scope

The Shanghai metropolitan area is in the middle and lower reaches of the Yangtze River and is one of the first batches of urban planning officially approved by the China Development and Reform Commission, with an important strategic position [44,45]. China Development and Reform Commission is the decision-making unit that determines major development issues within a city. Urban planning is a statutory document that guides urban development. The first batches of urban planning represent the importance that the China Development and Reform Commission attaches to this planning achievement. In China, the higher the strategic level of a city, the more representative it is. This article takes the Shanghai metropolitan area as the research area, which has higher research representativeness and demonstration value. This study takes the Shanghai metropolitan core area as the research area. It includes 8 Prefecture-level city units in Suzhou, Wuxi, Changzhou, and Nantong of Jiangsu Province, and Huzhou, Jiaxing, Ningbo, and Zhoushan of Zhejiang Province. Street (township) is one of the administrative divisions in China, and the street office (town government) is the smallest agency of the state for the local area spatial governance, with legal management power over various land features within its jurisdiction. In China's urban management system, prefecture-level cities govern county-level cities, and county-level cities govern townships. Therefore, township boundaries are defined within the boundaries of the city, with a detailed delineation of the minimum administrative jurisdiction. The study takes streets (townships) as the smallest unit of analysis, with a total of 2572 streets (townships) and a total area of 37,200 km^2. At the end of 2021, the permanent population was approximately 55.36 million (Figure 1). The 'Development Plan for Shanghai Metropolitan Area', released in 2022, focuses on promoting the co-construction and sharing of regional public service facilities, making the Shanghai Metropolitan Area a national model area for urbanisation development. Therefore, it is necessary to strengthen research on the travel characteristics of non-commuters in the Shanghai metropolitan area, explore the relationship between travel activities and the built environment, and better support planning implementation.

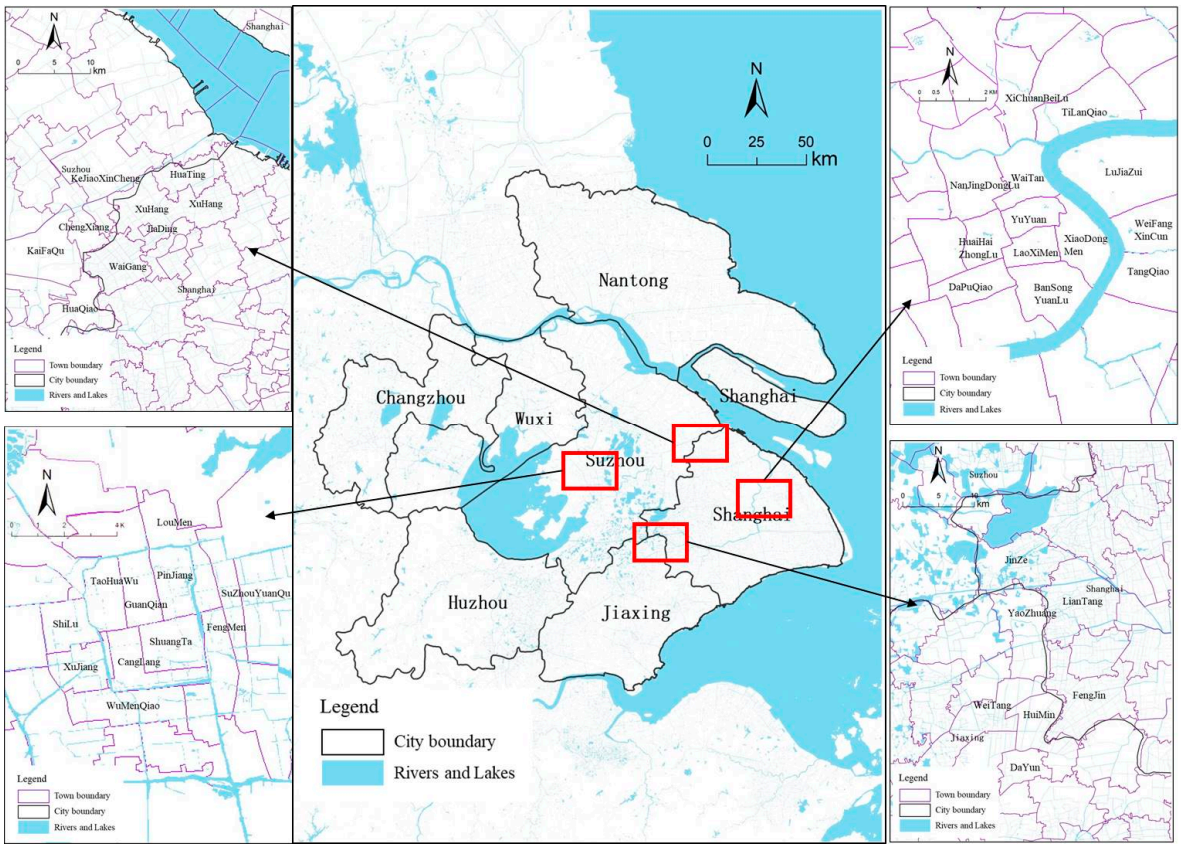


Figure 1. Study area and main towns.

Based on multi-source big data, this study explores the characteristics of residents' non-commuting flow and its interaction with the built environment. First, in this study, residents' non-commuting flow data and geographic spatial data were refined and extracted to construct a basic database. Second, social network analysis methods were used to measure residents' non-commuting flow patterns, identify the spatial heterogeneity of residents' non-commuting flow, and classify the functional types of streets and towns in different regions. Finally, this study used the GBDT to measure the nonlinear relationship between residents' non-commuting flow behaviour and the built environment within the spatial scope of the metropolitan area. It proposed policy recommendations and implementation strategies for the spatial planning of the metropolitan area.

2.2. Data Sources

The data required for this study include geospatial data, mobile signalling data, survey data on residents' travel behaviour, and data on residents' socio-economic attributes. The geospatial data include POI data (facility interest point data) and road network data. The POI data are sourced from Baidu Electronic Map. We applied to Baidu Company for data and obtained data on 24 types of facilities registered on the Baidu Electronic Map platform, including shopping malls, hospitals, hotels, and scenic spots. As of March 2023, there were a total of 587,812 POI sample points. This study starts from the OpenStreetMap electronic map website (https://www.openstreetmap.org/, accessed on 25 March 2023). We obtained road network data of Shanghai and surrounding metropolitan areas through public download. The collected electronic map data were pre-processed via geographic registration, spatial placement, and attribute verification, and the dataset was stored.

The mobile signalling data was sourced from the data integration platform of Chinese mobile phone operators. Data collection was from 11 to 25 March 2023. The signalling data includes information such as recording timestamps, starting and ending points of trajecto-

ries, transportation modes, number of sample users, and number of expanded users. We combined location information with residents' daily habits to comprehensively determine the type of non-commuting flow for residents. First, we selected the time period between 21:00 on the same day and 8:00 the following day as the basis for determining the place of residence; the time window between 9:00 and 17:00 was used to determine the workplace. We calculated the cumulative observed time of mobile phone users and identified the area with the highest cumulative ranking and user frequency exceeding ten times the user's place of residence or work. We referred to relevant definitions and empirical conclusions derived from previous research [28,29] and considered the 'pendulum-like' transportation behaviour between residence and workplace as commuting travel while defining other transportation behaviours as non-commuting flow. Commuting behaviour refers to the designated period of travel between the place of residence and the place of work/study and beyond the boundaries of people's residential communities. In metropolitan areas, a job-residence relationship exists between the central urban areas and the surrounding suburbs, resulting in cross-regional commuting behaviour. Furthermore, we estimated the total size of the permanent population in the study area based on the expansion algorithm of 'proportion of mobile phone users in the permanent population' and then extracted the number of non-commuting groups in the area on weekends. The total number of people in the Shanghai metropolitan core area was approximately 58.72 million, measured based on the mobile user expansion method. This figure is similar to the finding of 55.36 million permanent residents in the Shanghai metropolitan core area in the national demographic survey report, indicating that using this method to measure the expanded population data within the Shanghai metropolitan core area is basically accurate [30].

2.3. Variables and Indicators

Significant differences exist in each street (township) within the study area. To eliminate the impact of differences in the administrative unit area on the analysis results, this study selected the size of the non-commuting population within 1 square kilometre per unit area as the dependent variable. It estimated the total population size based on the expansion algorithm of mobile signalling data. According to the regional travel theory, population mobility is the main interaction between urban and regional factors. Based on this, researchers have constructed a comprehensive evaluation model for travel decision-making [31]. Previous studies have analysed the correlation between different built environment elements and residents' travel activities [31]. The content includes the density [2,5,9,17], diversity [5,16], and accessibility [4,9,17] of large-scale service facilities such as commercial facilities, medical facilities, educational facilities, sports and leisure facilities, and tourist attractions. Some studies suggested that built environment factors such as road network and intersection density [9,19] can promote or inhibit residents' travel. Therefore, the independent variable in this study mainly measured the construction level of various facilities within the research unit.

This study categorised facilities based on their level, including 12 indicators such as the densities of catering service facilities, large medical facilities, large shopping malls, large cultural facilities, large tourist attractions, parks and squares, bus stops, parking lots, and road networks, and the average travel time and average travel distance of residents. The details of each variable are shown in Table 1. This study obtained facility spatial location and related attribute information via Baidu electronic maps. We used the Baidu path calculation model to obtain the time and distance of non-commuting flow for residents.

Table 1. Variables and descriptive statistics.

Type	Variable Name/Unit	Definition	Mean	Standard Deviation
Commercial and cultural facilities	Density of small catering service facilities (n/km^2)	Number of small catering service facilities per unit area, including three types of facilities: food stalls, fast food restaurants, and convenience stores	30.743	214.51
	Density of large commercial complexes (n/km^2)	The number of large shopping malls per unit area mainly refers to large commercial complexes	9.424	14.37
	Density of large entertainment venues (n/km^2)	Number of large entertainment venues per unit area, including sports venues, entertainment venues, leisure venues, and cinemas	0.291	0.98
Transport infrastructure	Bus stop density (n/km^2)	Number of bus stops per unit area	0.982	1.88
	Parking lot density (n/km^2)	Number of parking lots per unit area	9.836	146.81
	Road network density (km/km^2)	Length of road network per unit area	6.819	17.31
Public service facilities	Density of large cultural facilities (n/km^2)	Number of large-scale cultural facilities per unit area, including nine types of facilities such as memorial halls, museums, exhibition halls, exhibition centres, and art galleries	3.613	9.10
	Density of urban park Density of urban park (n/km^2)	Number of park square facilities per unit area, including parks and small and medium-sized square facilities	0.470	2.20
	Density of tourist scenic Density of tourist scenic (n/km^2)	Number of large tourist scenic spots per unit area, including resort and scenic area facilities	6.849	32.15
	Density of large medical facilities (n/km^2)	Number of large medical facilities per unit area, including comprehensive hospitals and specialised hospitals	2.479	4.31
Non-commuting behaviour	Average travel distance/km	The average distance of non-commuting flow for residents, including the average travel distance within the city and the average travel distance between cities	0.523	0.29
	Average travel time/min	The average non-commuting flow time of residents, including the average travel time within the city and the average travel time between cities	32.5	3.78

Notes: Unit area refers to 1 square kilometre.

2.4. Research Methods

2.4.1. Gradient Boosting Decision Tree Model

In this study, the GBDT method was used for modelling analysis. GBDT is a machine learning algorithm [32] proposed by Tianqi Chen and is a type of decision tree. In recent years, this algorithm has been widely used in research fields such as urban space contraction [34], residents' travel satisfaction [35], and social differentiation caused by spatial mismatch [33]. Specifically, this is an integrated algorithm composed of decision trees. The model learns parameters using the Newton method, randomly and with dropouts, extracting N training samples from the training set as the training set for the tree. The model utilises the training set for iterative analysis, obtains M sub-models using training,

and then uses the average of the model calculation results as the regression prediction value. The model [36] can be represented as:

$$Loss(i) = \sum x \in node \frac{1}{2}\left(Fx - \hat{F}x, i-1\right)^2 \quad (1)$$

In the formula, $Loss(i)$ represents the combined classification model, Fx represents a single decision tree classification model. The gradient is $\left(Fx - \hat{F}x, i-1\right)$ and represents the residual value, which is the value of the current leaf node. $node\frac{1}{2}\left(Fx - \hat{F}x, i-1\right)^2$ is the annotation function. Compared with other machine learning models, the GBDT has the advantage that it is not prone to overfitting with no dimension reduction, high robustness, and high stability of results. The advantage of GBDT lies in its use of Newton's method to make the model more stable, supporting the parallel computation of feature dimensions, fitting missing values, and adding regularisation terms to prevent overfitting. Compared with traditional linear regression models, this model can effectively explain the nonlinear relationships between variables and visually express them as dependency graphs. Since the parameter setting of the GBDT model can directly affect the model effect, it is necessary to optimise the model using a parameter optimisation combination. The important parameters of GBDT are F_ DS (number of decision trees in the model), S_ DM (maximum depth of decision tree), N_ DC (node division standard), and M_ DN (minimum number of samples that a node can divide). Finally, we traversed the parameter combinations in the model, effectively avoiding a decrease in parameter accuracy while improving the efficiency of parameter optimisation and obtaining the optimal parameter configuration scheme for a specific model.

2.4.2. Weighted Entry Centrality Analysis

The degree centrality index is used to characterise the importance of nodes in the network. In weighted directed flow networks, degree centrality can be divided into two types of indicators: weighted in degree and weighted out degree. To better reflect the characteristics of non-commuting flow, the weighted centrality index was selected. Of these characteristics, nodes represented various streets (towns) in the Shanghai metropolitan area, edges represented the non-commuting pedestrian flow connections between each street (town), and the weight of the edges was the number of non-commuting population attracted by each street (town) per unit area. The specific formula is as follows:

$$N_i = \sum_{x=1}^{n} S_{xy} r_{xy,xn} \quad (2)$$

In the equation, N_i represents the weighted centrality of node x, S_{xy} represents the weight of the edges between node y and node x, $r_{xy,xn}$ represents the number of directed edges between node y and node x, and n represents the number of nodes associated with node x.

3. Results

3.1. Spatial Characteristics of Non-Commuting Flow in the Core Area of Shanghai Metropolitan

This study divided the centrality of the two 'street township' levels into four categories based on the natural breakpoint classification method. We took the lower limit of the third class as the boundary and divided the functional types of streets (towns) into urban and intercity travel networks. A proportion greater than the threshold indicated that the street (township) could attract a larger non-commuting population. Based on this, the types of streets (towns) in the Shanghai metropolitan core area were divided into three categories, including internal inflow (attracting more non-commuting populations within cities), external inflow (attracting more non-commuting populations between cities), comprehensive inflow (attracting more non-commuting populations within and between cities) as shown in Table 2. The above types included 11, 14, and 14 streets (townships), respectively (Figure 2). Significant differences existed in the spatial distribution of different

functional types of streets (towns). The comprehensive inflow-type streets (towns) were mainly distributed in the main urban area of Shanghai, the internal inflow-type streets (towns) were mainly distributed in the main urban area of Suzhou, and the external inflow-type streets (towns) were mainly distributed in the adjacent areas between Shanghai and surrounding cities.

Table 2. Non-commuting flow characteristics of typical streets (towns) in the Shanghai metropolitan core area.

Type	Name	Affiliation	Weighted Entry Centrality (within the City)	Weighted Entry Centrality (between Cities)	Notes
Internal inflow	Pingjiang Subdistrict	Suzhou	449.15	0.48	We divided the centrality of the two 'street township' levels into four categories by weighted entry centrality. The first class is above 800 (within the city) and below 0.3 (between cities); The second class is 400–800 (within the city) and 0.3–0.5 (between cities); The third class is 100–400 (within the city) and 0.5–0.7 (between cities); The fourth class is below 100 (within the city) and above 0.7 (between cities).
	Canglang Subdistrict	Suzhou	438.63	0.31	
	Guanqian Subdistrict	Suzhou	354.03	0.43	
	Shuangtang Street	Suzhou	422.37	0.62	
	Nanjing East Road Street	Shanghai	332.19	0.72	
	Tangqiao Street	Shanghai	410.71	0.41	
External inflow	Chengxiang Town	Suzhou	83.72	1.06	
	Kunshan Development Zone	Suzhou	28.73	1.18	
	Waigang Town	Shanghai	12.81	0.82	
	Jingzhe Town	Suzhou	79.02	0.49	
	Weitang Town	Jiaxing	13.87	0.38	
	Huimin Town	Jiaxing	19.13	0.85	
Comprehensive inflow	Waitan Subdistrict	Shanghai	1267.34	0.82	
	Yuyuan Subdistrict	Shanghai	805.18	0.67	
	Laomenxi Subdistrict	Shanghai	839.21	0.92	
	Lujiazui Subdistrict	Shanghai	757.68	1.56	
	Weifangxincun Subdistrict	Shanghai	359.17	0.78	

Based on the residents' non-commuting characteristics within and between cities, we divide streets (townships) into three categories: internal inflow streets, external inflow streets and comprehensive inflow streets. In Figures 1 and 2, the streets (townships) with significant non-commuting characteristics are classified and expressed, which are mainly clustered in four sub-regions within the study area. These streets (towns) are mainly concentrated in the urban areas of Shanghai, Suzhou, the border area between Shanghai and Suzhou, and the border area between Shanghai and Jiaxing. Shanghai and Suzhou are both megacities in China, with a population of over 10 million in their main urban areas. The high level of public service facilities and commercial entertainment facilities in the urban areas have a significant attraction for non-commuting travel of residents in surrounding areas [17]. In the border area between Shanghai, Suzhou, and Jiaxing, non-commuting flows exhibit a bidirectional connection feature from Suzhou, Jiaxing to Shanghai, indicating frequent cross-regional non-commuting activities in the border area. These streets (townships) were the areas selected for in-depth analysis.

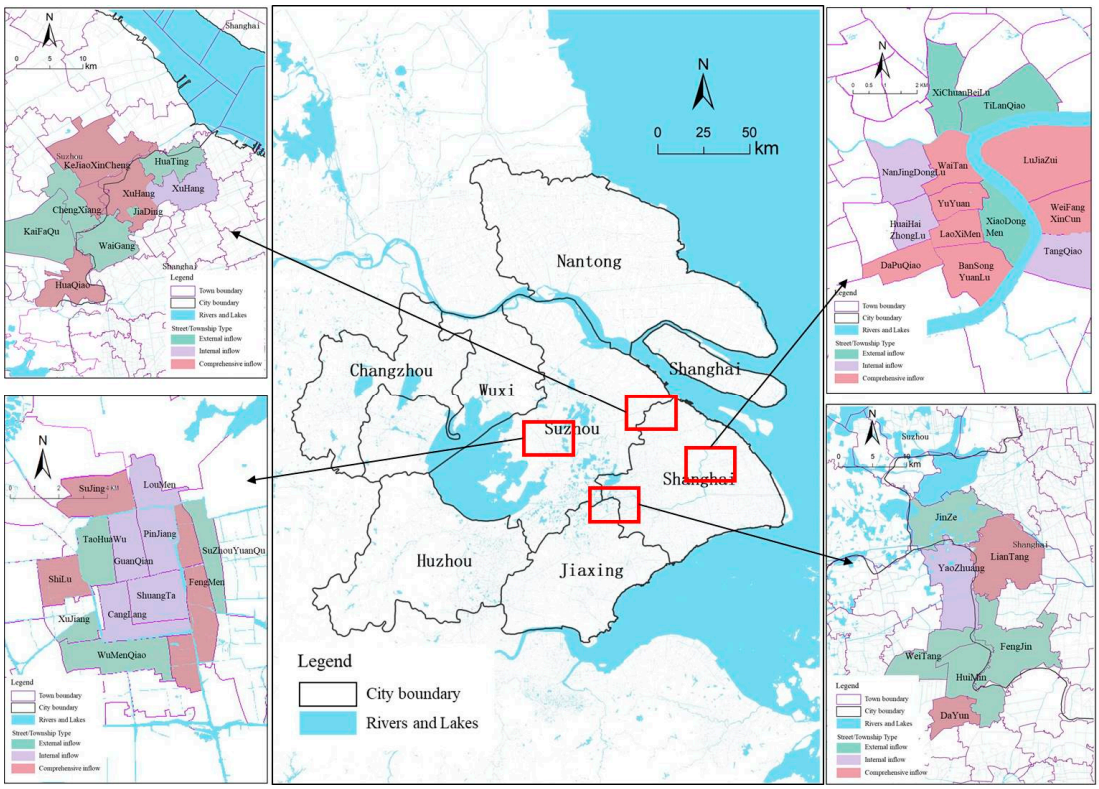


Figure 2. Spatial characteristics of non-commuting flow in Shanghai metropolitan core area.

The inflow of non-commuting flow networks in the Shanghai metropolitan area cities is concentrated in the central urban areas of each city. Shanghai is the region with the most active flow of non-commuters in the city, including 9 of the top 10 streets with weighted entry centralities, such as Lujiazui Street, Bund Street, and Nanjing East Road Street. These areas are traditional commercial, medical, and leisure service centres in Shanghai, with a high density of public service facilities and a strong ability to gather a non-commuting population. Suzhou and Jiaxing occupied second place, followed by other cities. In addition, at the urban scale, non-commuting flow within the city showed a decreasing trend from the central urban area to the peripheral areas, consistent with the public service facilities and population distribution pattern of various cities in the Shanghai metropolitan core area.

Compared with the intra-city non-commuting flow, the inter-city non-commuting flow in the Shanghai metropolitan area was concentrated in the urban junction area and the main urban area of Shanghai. A cross-city non-commuting flow cluster has been formed spatially, with Shanghai as the core and extending towards the region's hinterland. Specifically, there were clusters of non-commuting flows in areas such as Shanghai Kunshan and Shanghai Jiaxing. Suzhou Science and Education Area, Suzhou Development Zone, Weitang Town, and Humin Town were the main inflow areas for non-commuting flow between cities. These streets (towns) were active areas of population flow between cities, which may be attracted and radiated by the public services, transportation facilities and other infrastructure of nearby towns. This feature is also consistent with the development goals of provincial-level adjacent areas formulated in the 'Development Plan for Shanghai Metropolitan Area' policy. The main urban area of Shanghai is also the main inflow of non-commuting flow in the region. The construction level of public service facilities and the density of the public transport network in the region are at the highest level. To a certain extent, the absolute advantage of the facility level offsets the attenuation of attraction caused by the space distance.

3.2. Gradient Boosted Decision Tree Has a Better Fitting Effect Than Multiple Linear Regression Model

First, this study used the variance expansion test to test the factor independence of independent variables and found that 'small shopping service facilities, small medical service facilities', and other independent variables had strong multicollinearity (VIF > 10). Therefore, the model eliminated the collinearity variables mentioned above and retained other independent variables to form a set of variables. On this basis, the randomised search cross-validation method and ten-fold cross-validation were used to build the GBDT model. The results showed that, compared with the multiple linear regression model, the GBDT constructed in this study has a better regression fit, particularly for the fitting effect of urban residents' non-commuting flow.

In addition, from the regression results of the two models (Table 3). The significant positive correlation was identified between non-commuting flow in cities and the density of large commercial complexes, large medical facilities, parking lot density, and density of urban parks, while a negative correlation was found with average travel distance and average travel time. There was a positive correlation among non-commuting flow between cities and road network density, parking facility density, and density of urban parks and a negative correlation between average travel distance and average travel time. The results of the two models showed relative consistency, although differences in the significance of some variables were identified. Overall, the gradient upgrade decision tree model has a better fitting effect on the influencing factors of residents' non-commuting flow.

Table 3. Fitting effect between gradient boosting decision tree model and multiple linear regression model.

Impact Factors		R^2 (Non-Commuting within the City)		R^2 (Non-Commuting between Cities)	
Classification	**Name**	**GBDT**	**Multiple Linear Regression**	**GBDT**	**Multiple Linear Regression**
Commercial and cultural facilities	Density of small catering service facilities	0.0031	0.0001	-8.672×10^{-3}	-8.534×10^{-7}
	Density of large entertainment venues	0.0168	−0.0037	0.0318 **	−0.0009 *
	Density of large commercial complexes	0.1729 ***	0.0821 *	0.0718 **	0.0026 **
Transport infrastructure	Bus stop density	0.0628	−0.0036 *	-9.078×10^{-2} **	-8.785×10^{-4} *
	Parking lot density	0.2667 ***	0.0721 *	-4.382×10^{-3} **	-4.098×10^{-5} *
	Road network density	4.621×10^{-1}	4.371×10^{-3}	-1.172×10^{-2} ***	-0.081×10^{-6} ***
Public service facilities	Density of tourist scenic Density of tourist scenic	0.0398 ***	0.0191 *	0.1054	0.0339
	Density of large medical facilities	0.4596 ***	0.2312 *	0.7262	0.1823
	Density of large cultural facilities	0.0572 **	0.0381 **	0.0218	0.0082
	Density of urban park Density of urban park	0.0318 ***	0.0083 *	4.578×10^{-1} **	4.382×10^{-3} *
Non-commuting behaviour	Average travel distance	−0.2723 **	−0.1829 **	−0.4883 **	−0.2181 **
	Average travel time	−0.0438 *	−0.0182 *	−0.0171 *	−0.0078 *
Basic information about the model					
Constant		−7.332	−5.325	0.031	0.733
R-squared		0.908	0.731	0.782	0.524
Adjust R-squared		0.821	0.664	0.568	0.359

Note: *, **, ***, respectively represent $p < 0.05$, $p < 0.01$, and $p < 0.001$.

3.3. Large Medical Facilities and Commercial Complexes Are the Main Factors Attracting Non-Commuting Flow in Cities

The impact of large-scale public service facilities and transportation infrastructure is particularly significant among the various influencing factors of non-commuting flow within the city. We selected the top 8 influencing factors in the correlation ranking, measured the actual threshold of factor action, and drew a biased dependency graph (Figure 3). Due to sample limitations and model fitting accuracy, the bias dependence diagram may have local volatility when reflecting the correlation between the built environment and travel behaviour. Therefore, this study focused on analysing the overall trend when discussing the relationship between the two. Among these influencing factors, the contribution range of the distribution density of large medical service facilities to non-commuting flow volume was between 1300 and 1400 people, showing a positive correlation overall. Specifically, its nonlinear influence mechanism exhibited a significant threshold effect. There was almost no impact on the non-commuting flow in the 0.8 to 1.7 people/km^2 range. After reaching the 1.7 people/km^2 threshold, the non-commuting flow density attracted by large medical institutions rapidly increased from 1000 people/km^2 to 1200 people/km^2 (Table 4).

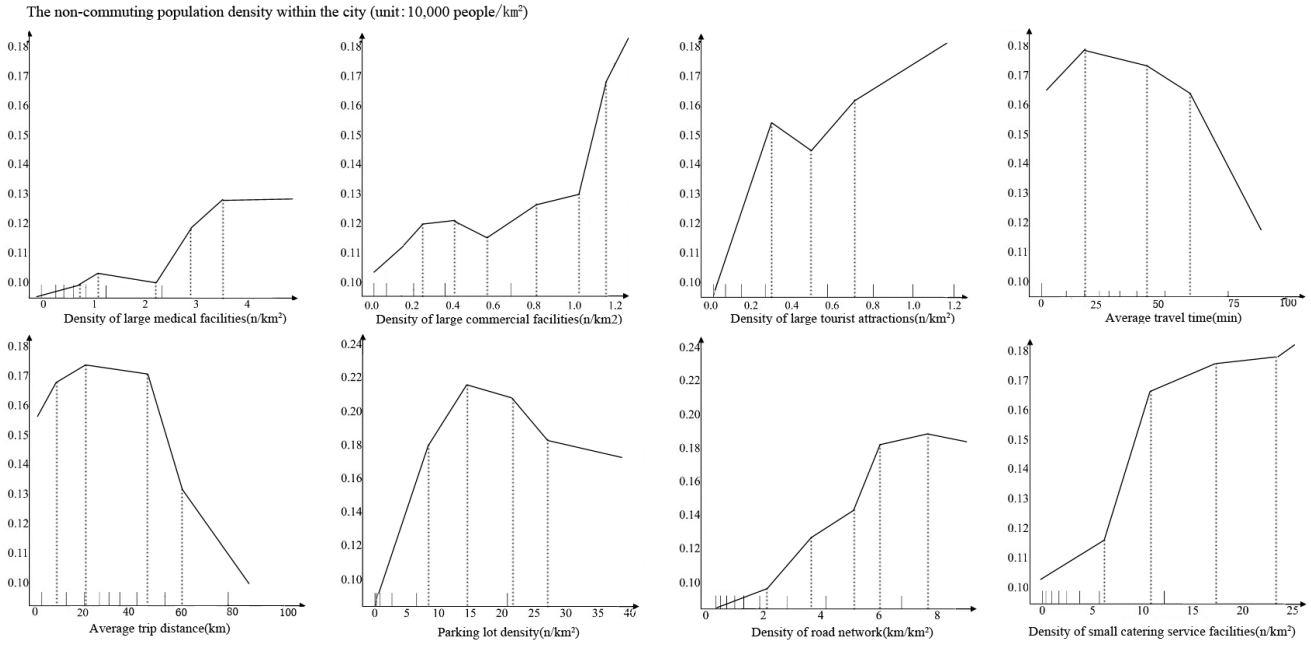


Figure 3. Partial dependence diagrams of non-commuting flow within the city.

Table 4. Relative importance ranking of independent variables in GBDT.

Variable		Non-Commuting within the City			Non-Commuting between Cities		
		Relative Importance	Comprehensive Ranking	Internal Sort	Relative Importance	Comprehensive Ranking	Internal Sort
Commercial and cultural facilities	Density of small catering service facilities	0.049	8	2	0.034	6	2
	Density of large entertainment venues	0.048	9	3	0.008	12	3
	Density of large commercial complexes	0.161	2	1	0.137	3	1

Table 4. *Cont.*

Variable		Non-Commuting within the City			Non-Commuting between Cities		
		Relative Importance	Comprehensive Ranking	Internal Sort	Relative Importance	Comprehensive Ranking	Internal Sort
Transport infrastructure	Bus stop density	0.022	12	3	0.017	11	3
	Parking density	0.052	6	1	0.302	2	2
	Road network density	0.051	7	2	0.309	1	1
Public service facilities	Density of tourist scenic	0.157	3	2	0.018	10	4
	Density of large medical facilities	0.185	1	1	0.027	8	3
	Density of large cultural facilities	0.042	10	3	0.022	9	2
	Density of urban park	0.027	11	4	0.031	7	1
Non-commuting behaviour	Average travel distance	0.095	5	2	0.054	4	1
	Average travel time	0.110	4	1	0.041	5	2

3.4. Impact of Transportation Infrastructure on Non-Commuting Flow within the City Shows a Significant Threshold Effect

The road network density was positively correlated with the non-commuting flow within the city and showed a significant threshold effect. Within the ranges of 2.1–3.8 km/km^2 and 5.1–5.6 km/km^2, this factor had the most significant impact on non-commuting flow, with the non-commuting flow density at the street (township) scale rapidly increasing from 1000 people/km^2 to 1800 people/km^2. This result was consistent with existing research findings [16]. The increase in road network density effectively enhanced road network connectivity and improved the walkability of streets (towns). However, in the range of 6.3–8.2 km/km^2, its impact gradually reduced, and the increase in road network density did not significantly increase the attraction of non-commuting flow in the region, reflecting the threshold effect in local areas. Excessive road network density may reduce the proportion of other facilities, affecting the attraction to non-commuting flows (Figure 3).

Among the various influencing factors of non-commuting flow among urban residents, road network density had the greatest impact (27.3%), followed by parking facility density, large medical facility density, and average travel distance. Compared to public service facilities (26.7%), transportation and supporting facilities (42.1%) can significantly affect non-commuting flow among urban residents. In addition, convenient community-level daily service facilities had a greater impact on the non-commuting flow between cities than large facilities. The well-established transportation infrastructure in neighbouring towns can meet residents' diverse and convenient travel needs in the surrounding area, thereby increasing the non-commuting flow between cities. Meanwhile, comprehensive community-level public service facilities can provide residents with a better service experience in a short period of time, which is consistent with the existing research [37,38]. We selected the top 8 influencing factors for analysis and plotted their partial dependence graph (Figure 4).

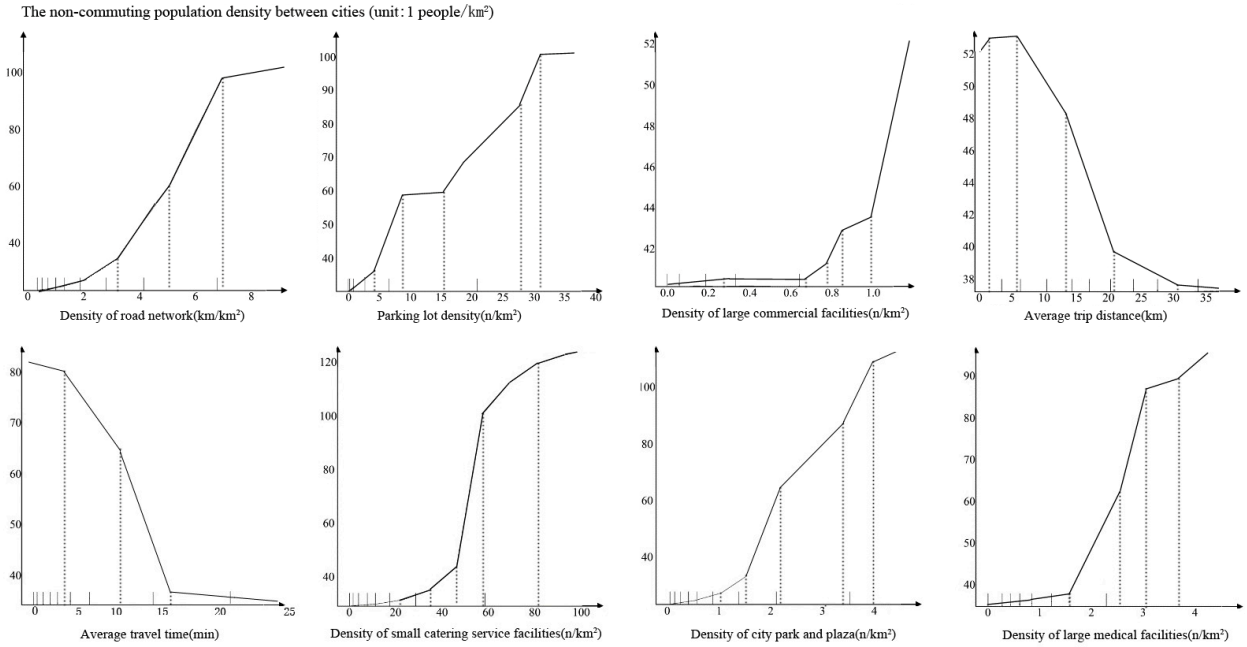


Figure 4. Partial dependence diagrams of non-commuting flow between cities.

4. Discussion

4.1. Transportation Infrastructure Is the Main Factor Affecting Non-Commuting Flow between Cities

The results indicate that both road network density and parking lot density have a significant promoting effect on the non-commuting flow between cities, although there are certain differences in these two types of impact mechanisms. In the 0–7 km/km^2 range, this indicator is significantly positively correlated with non-commuting flow between cities. When the road network density exceeded 7 km/km^2, the correlation between the two was not significant, and an upper threshold effect was noted. The impact of parking lot density on non-commuting flow has a significant effect range, which was determined as 0–10/km^2 and 15–32/km^2, respectively. The non-commuting flow between cities is rapidly increasing within these two functional ranges. When the density of the parking lot reached approximately 35/km^2, the non-commuting flow reached the upper threshold. The possible reason is that after the construction in rural areas is completed, the density of local parking facilities and road networks is relatively stable, and there is an upper limit on the overall scale of receiving the residents from other cities. The possibility of further increasing the density of facility construction is relatively small, and the marginal effect of attraction on the non-commuting flow between cities is significantly reduced. The existing research results are similar to ours, and scholars have found that the layout density of urban infrastructure and public service facilities has a fixed threshold [39]. Within the threshold range, there is an upper limit to the service-carrying capacity of facilities for residents [40]. This conclusion is similar to existing research results. Sarkar constructed a regression model for urban morphology and commuting behaviour, exploring the impact of land use mixing on commuting time and distance [49]. The results showed that the higher the distribution density of transportation facilities, the higher the frequency and efficiency of commuting, and there was a significant positive correlation between the two factors. Hou studied the impact of a multi-centre city structure on the non-commuting travel frequency of residents under different transportation modes [39] and found that a multi-centre city structure helps to improve non-commuting travel time and frequency of residents and promotes residents' willingness to commuting travel.

The impact factor similar to the effect of road network density is also the density of parking facilities, which can effectively increase the non-commuting flow of urban

residents within the range of 0–15/km^2. Currently, the urban population in China has a relatively high level of car ownership, and residents are more inclined to use cars for non-commuting flow. The increase in the density of parking facilities is beneficial for attracting non-commuting flow within the city. However, when the density of parking facilities exceeded the threshold of 15/km^2, the attractiveness of streets with a high density of parking facilities decreased instead of increasing. A possible reason is that the upper limit of the carrying capacity of public service facilities has been reached, and the population attraction per unit area is saturated.

4.2. Residents' Travel Time and Distance Are Significantly Affecting Non-Commuting Flow between Cities

The average travel distance of residents also showed a significant inverted 'U' shaped feature. When the travel distance increased from 0 km to 7 km, the non-commuting flow between cities remained at 52 people/km^2. When the travel distance increased from 7 km to 30 km, the attractiveness of streets (towns) to the non-commuting flow in the surrounding area rapidly decreased, from 52 people/km^2 to 35 people/km^2. Similarly, when the travel time increases from 5 min to 25 min, the non-commuting flow between cities shows a significant decrease. Non-commuting flow between cities is more sensitive to time factors, and 0.5 h is an effective threshold range for maintaining pedestrian flow in neighbouring towns.

Furthermore, the average travel distance of residents and non-commuting flow volume showed an inverted 'U' shaped correlation, and the relative importance of indicator features was 0.022. When the travel distance increases from 20 km to 80 km, the non-commuting flow volume decreases to around 1000 people/km^2. These results indicate that non-commuting flow within cities is more sensitive to distance factors, and residents prefer short-distance travel. The relationship between the average travel time of residents and non-commuting flow volume can also confirm this conclusion. When the non-commuting flow time between residents in cities increased from 25 min to 90 min, the attractiveness of the non-commuting flow in the area decreased from 1800 people/km^2 to 1200 people/km^2. This finding indicates that the active travel distance range within the city in the metropolitan area is between 20 km and 40 km. A possible reason is that the infrastructure of various cities within the Shanghai metropolitan area is mature and complete. Residents in suburban streets (towns) can reach the city's high-level public service centre within 40 kilometres, and residents are more inclined to choose high-level facilities. This conclusion is similar to existing research. A study on the behaviour of commuters in Hong Kong, China, found that residents prefer to choose higher-level facilities within the 30–40 min range by car [42]. This conclusion is similar to existing research, and some scholars have explored the impact of spatial attributes of the built environment around residential areas on non-commuting travel preferences and decisions [32]. The results showed that in terms of personal and family non-commuting travel willingness, the longer the travel time and distance of residents, the significantly decreasing trend of non-commuting travel willingness and frequency [35]. The 30-min or 20-kilometre range is the appropriate time and distance range for non-commuting travel by residents [36].

4.3. Impact Mechanism of Public Service Facilities on Non-Commuting between Cities Is Relatively Complex

The relative importance of the density of daily public service facilities was higher than that of large facilities. Among them, the density of large shopping malls, small catering service facilities, parks and squares, and large medical facilities were positively correlated with the dependent variable, but there were significant differences in the action intervals of different factors. The mechanism of action of large medical facility density and large shopping mall density was relatively similar. These two types of indicators had a strong nonlinear effect between 2–5/km^2 and 0.9–1.2/km^2, respectively, improving the attraction of non-commuting traffic to the street (township), although the effect was not significant in other sections. The purpose of non-commuting flow between cities is strong, and the

agglomeration effect of large public service facilities on pedestrian flow is higher than that of small community service facilities. High-level public facilities can undertake more regional service functions, which is conducive to attracting more non-commuting people between cities. The nonlinear impact of the density of catering service facilities and the density of parks and squares had an upper limit threshold, with positive effects ranging from 10 to 60/km^2 and 0 to 4/km^2, respectively. Within this range, non-commuting flow significantly increased, and the total volume remained constant thereafter. This is similar to the mechanism of the effect of public service facilities on non-commuting flow within the city. A possible reason for this finding is that because of the strong purpose of non-commuting flow between cities, the clustered park and square facilities often serve as regional social service centres, which can effectively attract non-commuting people from surrounding towns; however, the relatively large area of the park square has a negative impact on the layout of other public service facilities, which in turn has an upper limit on the total amount of non-commuting flow between cities.

This conclusion is similar to existing research. Engelfriet proposed multiple regional indicators to characterise the density of regional transportation facilities and the degree of mixing of various public service facilities and used this indicator system to study the relationship between the density of facility distribution in India's small cities and non-commuting shopping trips [50]. Research has found that the convenience of transportation facilities and the diversity of public service facilities are the main factors affecting residents' non-commuting shopping behaviour [50]. Diversified public service facilities can help increase residents' non-commuting time and frequency. There are also studies that hold different opinions. Some studies believe that the factors that affect non-commuting behaviour include the built environment, residents' socio-economic characteristics, residents' attitude preferences, lifestyle, and transportation ownership [51]. The diversity and convenience of public service facilities are important indicators for measuring the quality of built environments, and there is a threshold effect on the impact of facility diversity on non-commuting travel. After exceeding the upper threshold, the number of facilities arranged cannot significantly improve the frequency and efficiency of non-commuting travel [52].

4.4. Policy Suggestions and Implementation Strategies for the Planning of the Shanghai Metropolitan Area

This study focused on the nonlinear relationship between non-commuting flow and the built environment, emphasising the importance of nonlinear impact, and plays a reference role in regional facility planning and residents' travel guidance policy formulation. First, the government needs to strengthen the integrated construction of regional facilities. As the connections between cities within the metropolitan area continue to strengthen, traditional planning methods use static indicators for quantitative measurement, making it difficult to provide precise guidance for the facility construction process. Mobile signalling data can objectively reflect the characteristics of regional population mobility, and combined with operational data from other cities, it can help planning decision-makers to finely identify the characteristics and development trends of urban factor mobility.

Second, according to the attributes of streets (townships), the government must carry out a networked layout and differentiated configuration of public service facilities. The non-commuting flow characteristics of different streets (towns) in the Yangtze River Delta showed significant differences, indicating significant differences in the attractiveness of different towns to outsiders, and it is necessary to develop differentiated facility allocation strategies. Among them, external inflow streets (towns) need to improve the integration level of intercity transportation and long-distance travel efficiency, improve the level system of facility configuration, advocate for networked facility layout, and strengthen the accessibility and functional integrity of community-level service facilities [53]. Community service centres with an external inflow population as the main source generally have a service radius of around 3 to 5 km. Within this service radius, the facilities can effectively

gather foreign populations [54,55]. Internally, inflow streets (townships) need to build public service centres with large medical facilities and commercial complexes as the core, strengthen the connection between large service facilities and bus stops, and strengthen population aggregation capacity through regional service centres. Townships (communities) located at the border of large cities generally have facility service radius set at intervals of 0.5 km to 1 km. Previous studies have shown that a sound facility network system is beneficial for residents to access more convenient services and facilitate non-commuting travel between cities [56,57]. Comprehensive streets (villages and towns) need to build a multi-level urban public service network based on daily service facilities and with large service facilities as the core and improve the urban public transport system's connection rate and connection efficiency (Figure 5).

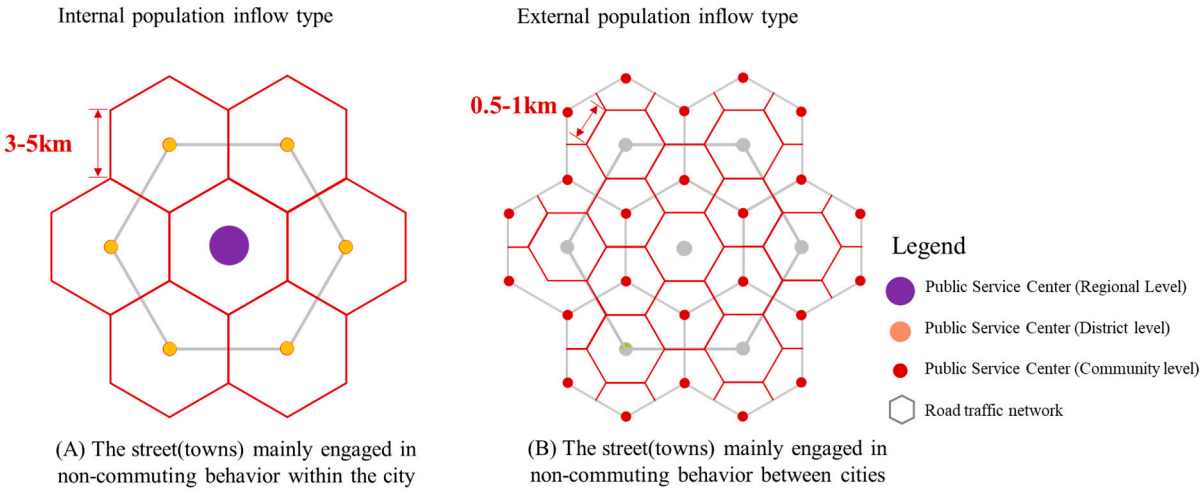


Figure 5. Regional public service network configuration models for different non-commuting flow types.

Finally, the planning should combine the threshold indicators and nonlinear impact mechanisms measured in this study to quantify the accuracy of various facility configurations within the metropolitan area. Taking large-scale medical facilities as an example, only when the concentration density of such facilities reaches 1.2 units/km^2 can the level of non-commuting flow be significantly improved. However, an upper limit of 4.2 indicators per km^2 was identified for leisure facilities such as parks and squares, and it is necessary to avoid duplicate construction to maximise the utilisation rate of the facilities.

5. Conclusions

5.1. Key Findings

Based on the Shanghai Metropolitan Area as an example, this study explored the characteristics of non-commuting flow and its nonlinear influencing factors within and between city residents by the GBDT model and other methods. The following four conclusions were made:

(1) The non-commuting flow within the Shanghai metropolitan area was concentrated in the main urban areas of each city, while the non-commuting flow between cities was concentrated in the surrounding towns and central urban areas of Suzhou. Among the four types of streets (towns), comprehensive streets (towns) were mainly distributed in the main urban area of Shanghai, internal flowing streets (towns) were mainly distributed in the main urban area of Suzhou, and external flowing streets (towns) were mainly distributed in adjacent areas between cities.

(2) Among the 12 independent variable indicators set in this study, we conducted a mechanism analysis on the top 8 indicators that had a significant impact on non-commuting flow. There are differences in the impact mechanisms of different factors within and between

cities. Non-commuting between cities was mainly concentrated in suburban township areas, subject to the dual nonlinear effects of transportation infrastructure and small public service facilities. However, the non-commuting flow within cities was mainly influenced by the nonlinear effects of travel distance and transportation environment, as well as the impact of large public service facilities.

(3) Among the various influencing factors of non-commuting flow within the city, large medical facilities and commercial complexes were the main factors that attract non-commuting flow. The impact of transportation service facilities on non-commuting flow in cities showed a significant threshold effect, and an excessively high road network density may reduce the proportion of other facilities, thereby reducing the attraction to non-commuting populations. Improving the density of parking facilities is beneficial for attracting the non-commuting population within the city. However, when the density of parking facilities exceeds the threshold of $15/km^2$, the attractiveness of streets with a high density of parking facilities decreases instead of increasing. In addition, the average travel distance of residents is inversely "U-shaped" related to non-commuting flow volume, with a distance range of around 20 km to 40 km being the most active range for population mobility within urban agglomerations.

(4) Among various influencing factors of non-commuting flow among urban residents, road network density had the greatest impact (27.3%), followed by parking facility density, large medical facility density, and average travel distance. This indicates that compared to public service facilities (26.7%), transportation and supporting facilities (42.1%) can significantly affect non-commuting flow among urban residents between cities. The relative importance of the density of daily public service facilities was higher than that of large facilities. The density of large shopping malls, small catering service facilities, parks and squares, and large medical facilities were positively correlated with the dependent variable, although there were significant differences in the action intervals of different factors.

5.2. Implications

This study analysed the travel characteristics of the non-commuting population in the Shanghai Metropolitan Area and explored the nonlinear relationship between the built environment elements and non-commuting flow through the gradient upgrade decision tree model. The research results have important guiding value for exploring intercity residents' travel characteristics at the regional scale and the spatial layout of regional public service facilities. This study compensates for the limitations of existing research on residents' travel that focuses on commuting behaviour within cities. It comprehensively identified the characteristics of non-commuting travel from both regional and urban levels and divided the functional levels and positioning of each block (township) within the metropolitan area from a travel perspective. Furthermore, this study enriches the multi-type relationship between the built environment and residents' travel behaviour and complements and verifies the practical application value of the nonlinear model for residents' travel behaviour pattern recognition.

5.3. Limitations and Future Research Directions

This study has some limitations. First, big data are desensitised data, and it is difficult for big data analysis to precisely identify individual information such as socio-economic attributes, and we only identify the residents' travel characteristics at the group level. In future studies, we will combine the mobile signalling data with the social survey data to further analyse whether there is an interaction between the socio-economic attributes and the built environment and whether there is a common impact on residents' non-commuting travel. Previous research has discussed the content of relevant fields [58,59]. Second, due to the complex impact mechanism of non-commuting travel among residents and the threshold effect of facilities related to the daily living habits of residents [60], there are clear regional characteristics [61]. In addition, follow-up research is required to use different cities as examples to compare and analyse the nonlinear effects of similar impact factors to

more comprehensively verify the rationality of thresholds of the built environment and other impact factors.

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