



## Article

# Study on the Influence of the Built Environment and Personal Attributes on Commuting Distance: A Case Study of the Tianjin Central Area Divided by TAZ Units

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**Abstract:** Long commuting distances pose a significant challenge for many large cities, undermining the principles of sustainable urban development. The factors influencing urban commuting distances among residents are complex and necessitate hierarchical analysis. This study uses Tianjin, one of China's four municipalities, as a case study, employing transportation analysis zones (TAZ) as research units. We classify these units based on resident and working populations, extracting multiple built environment and personal attribute factors to establish a model that examines the influence of the job–housing balance. The analysis identifies 12 sub-items across two categories of influencing factors, with correlations tested through spatial analysis and linear regression. We found 28 positive associations and 35 negative associations. Notably, the job–housing relationship for the working population was generally more sensitive to changes than that of the resident population. At the TAZ level, personal attributes exerted a more significant influence on the job–housing balance than built environment factors, with commuting mode, life stage, age, and income level notably affecting commuting distances.

**Keywords:** commuting distance; job–housing relationship; sustainable development



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## 1. Introduction

Long-distance commuting is a prevalent issue in contemporary urban landscapes, reflecting the substantial spatial separation between where residents live and work. The job–housing relationship, to an extent, is an integral component of modern work–life balance, exerting a significant influence on an individual's quality of life and career progression. In 2022, the average commuting distances in China's megacities and large cities were 8.3 km and 7.4 km, respectively, with Beijing notably reaching 11.1 km [1]. These figures significantly surpass the threshold for a “happy commute”, which is typically defined as a distance of less than 5 km. Prolonged commuting distances engender a cascade of adverse effects: they contribute to chronic traffic congestion, exacerbate the challenges of traffic management, curtail citizens' daily activities, diminish urban vibrancy, and degrade the quality of life for residents. Concurrently, they precipitate a host of urban challenges, including increased fuel consumption and environmental pollution. The implications of the urban job–housing relationship are far-reaching. Hence, there is an imperative need for in-depth research into the urban job–housing nexus to establish a theoretical foundation for optimizing the urban job–housing structure.

The theoretical exploration of the job–residence nexus dates back to the 19th century, with Ebenezer Howard's proposal of the Garden City movement in England, which aimed

to address the burgeoning issues of high population density, chaotic urban transportation, and the proliferation of slums in London at that time. The urbanization process gained momentum in the 20th century, particularly following the Industrial Revolution, leading to a surge in urban challenges. Consequently, discourse on the work–housing relationship intensified, and several key concepts emerged, including the satellite city theory, organic evacuation theory, and job–housing displacement theory. The Machu Picchu Charter later introduced the concept of mixed-use development, underscoring the interconnectivity of urban functions. In the post-World War II era, the economies of Western developed countries experienced rapid growth, leading to a plethora of urban issues in many large cities due to swift economic and population expansion. This period also saw the rise of new urbanism, which explicitly defined “diversity” as a criterion and emphasized a multifunctional mix of land use. New urbanism advocates for the development of compact cities that support a vibrant living environment and retail activities through high population density, thereby encouraging residents to work closer to where they live. Guided by these theoretical frameworks, achieving a balance between work and residence has become a clear objective in modern urban planning and development.

By combing through the focus of current job–housing research, it is found that the focus of research in the academic community has shifted from the assessment of the current situation and the search for influencing factors to the exploration of influencing mechanisms, but the types of influencing factors in most discussions are relatively homogenous. In the Web of Science core collection, the indexing formula was successively restricted to job–housing (Topic) and influencing factors (Topic) and 2013–2024 (Year Published) and English (Language), and spatial mismatch (Topic) and influencing factors (Topic) and 2013–2024 (Year Published) and English (Language), taking the concatenation of the two indexing results. After removing irrelevant articles, 17 documents were obtained, as shown in Table 1. Through the synthesis and comparative analysis, the following results were found: (1) The relevant papers with impact factors as the research theme have had a growing trend in the last decade. (2) The fact that the current study focuses on Chinese cities suggests that Chinese cities have been plagued by occupational and residential spatial mismatches more recently and to a greater extent, while the study of Chinese cities can shed light on more developing countries. (3) The majority of the research objects are Beijing, and there is a lack of in-depth research on other cities. However, Beijing, as the political and economic center of China, has strong special characteristics, and the occupational and residential problems themselves have spatial heterogeneity [2–4], which means that the same factors may have different impacts on different spatial scales or geographic locations [5]. Therefore, we should extensively strengthen research on other cities, especially typical cities, in order to build up a database, which will help us to find out the rules, from status quo analysis to simulation and prediction. (4) The influencing factors of existing job–housing relationship studies can be broadly categorized as the built environment, policies, and personal attributes, with most studies focusing on only one category and with a lack of composite types of studies.

Urban built environment factors basically include city size and compactness, urban spatial structure, public transportation services, and land use mix. Factors include gender, age, ethnicity, educational background, income, availability of a private car, commuting mode, house prices, policies, and institutions, which are personal attribute factors. In terms of institutions and policies, China has some unique characteristics. The current research state on each influencing factor is briefly summarized below.

**Table 1.** Summary of the articles on job–housing, spatial mismatch, and influencing factors in the last 10 years on Web of Science.

Article Num	Published Year	Study Object	Influencing Factors Types		
			Urban Built Environment Factors	Politics Factors	Personal Attributes Factors
1 [6]	2024	Shanghai, China	✓		
2 [3]	2023	China	✓		✓
3 [7]	2022	Zoucheng, China			✓
4 [4]	2022	GuangZhou, China	✓		
5 [8]	2022	Tianjin, China		✓	
6 [9]	2021	Beijing, China	✓		
7 [10]	2020	Xiamen, China	✓		
8 [11]	2019	Benin metropolitan region	✓		
9 [12]	2019	Hangzhou, China	✓		
10 [13]	2018	Beijing, China		✓	
11 [14]	2017	Changchun, China		✓	✓
12 [15]	2017	China		✓	
13 [16]	2016	Beijing, China	✓		
14 [17]	2016	Beijing, China	✓		
15 [18]	2016	Guangzhou, China	✓		✓
16 [19]	2015	Beijing, China	✓		✓
17 [20]	2015	Beijing, China	✓		

✓: Study Object The category that it belongs to.

In terms of the size and compactness of the city, both population size and land size are positively correlated with commuting time, which is the main conclusion developed in the established studies. However, He Zhou et al. argue that the impact of urban compactness on commuting time consumption is twofold: on the one hand, compact cities will lead to a variety of daily activities being accomplished in a smaller area, helping to reduce commuting time, while on the other hand, over-densification can create traffic congestion and increase commuting time [21].

In terms of public transport services, Zhang Banghui et al. advocate that the occupational and residential situation should be optimized by improving the arrangement of public transport in peripheral areas of the city, guided by the tenet that public transport provision should be public first [22]. There are also studies that have come to the opposite conclusion: public transport systems lacking sufficient convenience can effectively limit the extent to which citizens can afford the commuting time, so that they have to give up jobs with excessively long public transport commuting times, which is conducive to the job–housing balance [23]. Studies on Beijing–Tianjin intercity railway commuting by Wang Zhen also support the view that increased accessibility of long-distance public transport may exacerbate work–life separation [24].

In terms of land use mix, increasing the degree of land use mix has been mentioned several times as a suggestion to optimize the job–housing relationship, but it has not attracted much discussion in its capacity as an influencing factor. By analyzing the mixing characteristics of typical employment areas in Shanghai, Tian et al. found that employment areas with more diverse land uses and that were located further away from the city center had higher internal commuting and were more likely to be self-balancing [25]. The joint role of location for mixed land use is not excluded from the conclusions of this study. The idea that localized mixed land use can internalize some of the city’s transport demand is also recognized in the study by Cao Kunzi et al. It is also pointed out that the effect of the mixing degree of land use on the number of miles travelled is influenced by the size of the study unit [26]. The impact of different land use functions was further explored, and it was found that spatial differences in education and healthcare resources were important factors affecting residents’ choices of residence locations [27].

In terms of educational background and income status, they often appear in pairs in discussions of job–housing issues, mainly for groups with low educational attainment and low incomes. The famous Spatial Mismatch Hypothesis is a study of low-income groups, which found that workplaces are often clustered in the center of the city, while residences are scattered in the peripheral areas of the city due to land prices, creating a reality mismatch between workplace and residence [28]. The theory has been repeatedly tested over the years [29]. However, Chinese scholars' interview-based analyses have come to the opposite conclusion in recent years: shantytown residents' educational background is negatively correlated with commuting distance [30,31]. It has also been demonstrated that the higher the income of the worker and the higher the average level of education, the longer the commute is [32].

In terms of the availability of a private car, it is also commonly explained with income. Higher-income groups tend to have a higher proportion of private car ownership [33,34]. As a result, they are also more flexible in their choice of place of employment, and in this way, they compensate for the negative impact of the spatial mismatch between work and residence on commuting [35].

In terms of age and gender, the main argument in China is whether there is a significant correlation with the job–housing relationship or not. Some scholars believe that ageing mainly represents a change in family roles, which leads to an increased reliance on public service facilities and thus affects work–life relationships [36]. However, in today's China, young people are no longer conforming to the rules, so the age at which it is appropriate to get married and have children has become much broader and difficult to correspond to directly.

In terms of commuting mode, Shen Lifan et al. found that public transportation commuting is positively correlated with commuting time consumption, while cycling and walking are negatively correlated with it, and commuting by car does not have a significant effect on it [37]. Some scholars believe that more efficient rail or shuttle bus services can attract more people to commute by public transport and alleviate the pressure on urban transportation [38]. In contrast, it has been shown that the construction of rail transit in most major cities has had a limited effect on the overall change in travel patterns. In particular, it is difficult to replace the stock of car trips, in which the proportion of residents traveling by car near subway stations is even higher than in other locations [34].

In terms of policies and institutions, the Housing Provident Fund, guaranteed housing policy, and the unique "Danwei" system in China are the focus of research [8]. According to one study, the housing fund and mortgage system help to meet the basic housing needs of citizens, but the provision of subsidized housing can play a decisive role in the housing problems of low-income groups. However, it solidifies their place of residence and creates a further mismatch between occupational and residential space [39]. This suggests that the housing security system in China still needs further regulation and refinement. Unfortunately, regarding data confidentiality, quantitative research on policy and institutional factors is very difficult in China, which largely hinders their optimization.

Although existing research has extensively discussed the influencing factors, there are also three issues that we hope to solve via this research.

One issue is that most research focuses on a single type of factor, and although there is good research depth, it is difficult to observe the overall situation. It is necessary to comprehensively consider the factors of urban construction and individual attributes to avoid the one-sidedness caused by analyzing a single type of factor from a single disciplinary perspective.

The second issue is that there are few existing studies that clearly define the scale of the research. For example, discussing the balance between residential and industrial land within the city will yield completely different results compared to discussing it at the scale of a certain industrial park area. It is necessary to choose appropriate research units and eliminate the interference of the research scale on the research results.



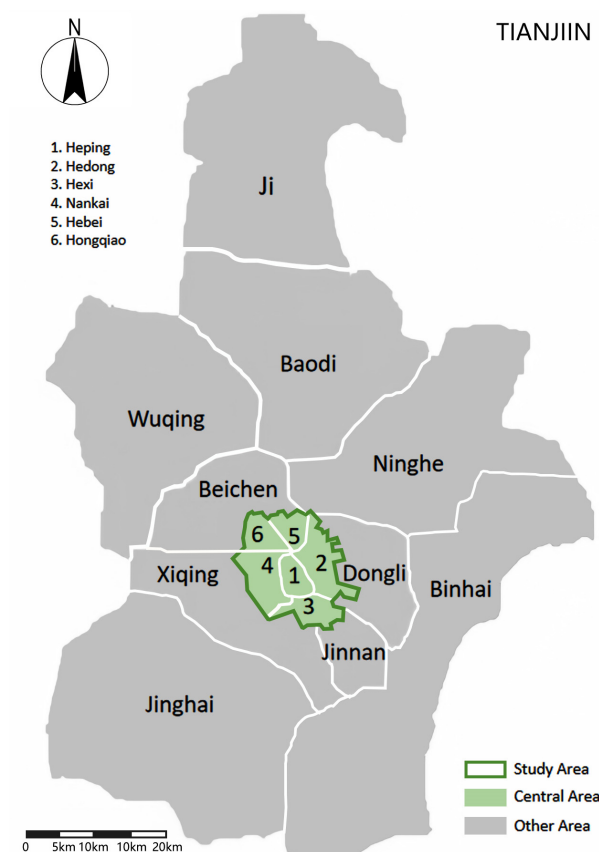
The third issue is the limitation of the research methods. Before 2010, most research in this topic was based on qualitative analysis. After that, some scholars started using questionnaires to collect data and analyze people's views on commuting, determining which factors will affect people's commuting time and distance based on the questionnaire data results. Around 2015, scholars began to be able to obtain data such as subway card swiping information to determine people's commuting routes. Geographic information systems can also be used to analyze which areas of the city have a high concentration of residents and which areas have a high concentration of workers. However, subways are not the only mode of transportation, and there has always been a lack of accurate data collection methods, resulting in insufficient accuracy in terms of commuting distance and difficulty in promoting quantitative correlation research between commuting distance and influencing factors. This is the main reason for restricting in-depth research on the issue of commuting-life balance. In recent years, with the development of big data, more diverse data platforms have emerged, such as using people's GPS location and time to obtain their living and working positions and subsequently their commuting distances. This study benefited from the development of data collection methods and conducted further analysis of influencing factors.

## 2. Materials and Methods

### 2.1. Study Area

Tianjin is an important economic center in northern China and one of the four municipalities directly under the central government in China, with an early start of urban development and rapid urbanization. Therefore, compared with other cities in China, Tianjin faced the spatial mismatch problem earlier and is represented in this study. At the end of 2023, Tianjin had a resident population of 13.64 million and a registered population of 11.5156 million. Among them, the permanent urban population is 11.66 million, and the permanent rural population is 1.98 million, with an urbanization rate of 85.49%. The population density of Tianjin is about 1140/km<sup>2</sup>, which is much higher than the average population density of 146.8/km<sup>2</sup> [40].

With the promotion of Beijing–Tianjin–Hebei synergistic development, the regional status of Tianjin has been increasing. The downtown area of Tianjin is the political, economic and cultural center of the city. According to the Tianjin Municipal Bureau of Statistics in 2019, the central urban area of Tianjin is the main employment area, encompassing the majority of employment opportunities, with only one-third of Tianjin's total population residing therein. In the past three years, the average one-way commuting distance in Tianjin has continued to rise, and the proportion of people commuting within 5 km has decreased [39]. Obviously, the occupational and residential spatial mismatch problem in Tianjin has to be analyzed and solved urgently. However, compared to the entire city of Tianjin, this study focuses only on six urban administrative districts in the city center without the rural area. Although Tianjin has a total area of 11,968 km<sup>2</sup>, as shown in Figure 1, the six central districts (Heping, Hedong, Hexi, Nankai, Hebei, Hongqiao) have long been considered the city's core and are the main source of job–housing balance issues. The remaining 10 districts, each larger than the combined area of the six inner districts, have much lower public transportation coverage, service points, and population density and were therefore not included in this study.



**Figure 1.** The location of the study area (the base map is from Baidu Map Insight).

## 2.2. Research Unit

In studies on the job–housing balance issue, it is common to divide units based on existing administrative divisions. The advantage of this approach is that the research findings can provide more direct references for regional development, and there is an abundance of data available, allowing for the use of national or regional public statistical information as a data foundation [41]. However, when choosing administrative divisions, using districts as units may result in an overly large scale. For instance, if the six districts in Tianjin’s city center were used as research units, the sample size would only be six, making it difficult to identify patterns. Therefore, it is necessary to find smaller research units.

A TAZ (transportation analysis zone) is an advantageous tool used for parsing complex traffic networks throughout a city: (1) similar traffic characteristics and strong traffic correlations within the same TAZ lead to the simplification of the complex network; (2) coordinated with the city control and management unit, the research results can be directly beneficial to the actual planning and management of the proposed recommendations. The study area is divided into 435 traffic analysis cells, and these are named with serial numbers.

## 2.3. Data Sources

In previous work–life studies containing personal attributes, the data source mainly relies on questionnaires, and smaller sample sizes are likely to have an impact on the accuracy of the results. This study avoids such problem by basing itself on the big data of personal attributes collected by the Baidu Map Insight platform, the commute monitoring big data platform module, and the big data platform module of urban population geography. The data sources represent the latest status of Tianjin’s population and commuting data as of April 2024. The one-way average commuting distance is used as the dependent variable to visualize the job–housing relationship through commuting. Then, using commuting distance as an evaluation index not only avoids the one-sidedness of traditional evaluation

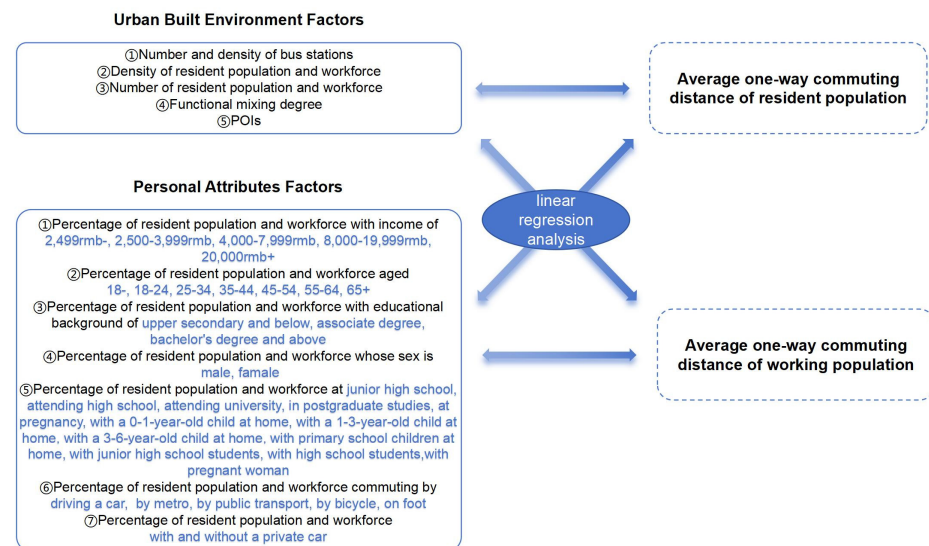
indexes such as the employment–resident population ratio, which only pursues a numerical equilibrium state and detaches itself from the actual situation, but it also prevents the arbitrary definition of residents’ employment areas by the Spatial Mismatch Index (SMI) and employment accessibility [42,43] under the perspective of the job–housing balance.

In the identification of residential and working populations, the platform uses users’ GPS positioning to make judgments. The working population refers to the population who have been working during the daytime for three consecutive months, who have mostly been located in office buildings or other locations with employment attributes, and who have had access to public WIFI and other conditions. The resident population refers to the population whose location is mostly in residential areas, with a single or non-public WIFI connection attribute, on weekdays, evenings, or weekends for three consecutive months. So, the current method is to use a mobile positioning system to identify the location where a person stays for more than 3 h during working hours as their workplace and the location where they stay for a long time during common rest periods as their residence. The travel behavior that connects the two places is defined as commuting behavior, which is usually illustrated as an Origin–Destination (OD) diagram.

#### 2.4. Study Methods

Given the numerous factors that influence commuting time and the fact that not all of these factors can be quantified numerically, a multivariate model is not suitable. In this study, we chose to use linear regression analysis to examine each influencing factor individually.

As shown in Figure 2, the independent variables were separately fitted to the  $AOCD_R$  (average one-way commuting distance of the residents) and  $AOCD_W$  (the average commuting distance of the workforce). Urban built environment factors were divided into 5 types of variables, and personal attributes factors were divided into 7 types of variables.



**Figure 2.** A flow chart of the comprehensive framework.

In regression results, such factors are considered to have a significant effect on the dependent variable, which are required to simultaneously satisfy the conditions that the value of  $R^2 > 0.5$ , the significance  $< 0.05$ , and the standardized residuals conform to the pattern of the histogram distribution. A positive or negative correlation is judged by fitting the slope of the equation. It should be noted that this study did not compare the correlation of different variables with commuting distance by this slope.

Screening and identification of influencing factors was a priority in the research process. By examining the causes of the formation of the job–housing mismatch and the related literature, combined with the actual data situation, such factors were filtered

out, which appeared with a high frequency in the established high-level literature. In the formation of the pattern of occupational and residential separation, China and the West have both commonalities and characteristics due to differences in their historical background, formation process, etc. By combining them, the common factors can be summarized as follows: policy and institutional adjustments [11,44,45], desire for a better living environment [11,46], development of the automobile industry [47–49], and urban evictions of low-income groups by land values [50,51].

The influencing factors that appeared more frequently (more than 3 times) in the established core literature were summarized, the objective conditions of whether the factor can be quantified, the logical reasoning of whether a factor is appropriate for the study under the perspective of TAZs, the actual situation of whether the data are publicized or not, and the reasons for the formation of the job–housing status quo were combined, and the factors that were related to the evaluation indexes, and so on, were removed to obtain the influencing factors for this study. The urban built environment factor contains urban public transportation [4,10,52], mixed land use [53–55], urban functional arrangement and industrial layout [56–58], population density [13,59,60], and population size [16,42], totaling 5 types of influencing factors. Personal attributes factors include income [31,45], age [61,62], educational background [9,63,64], gender [65,66], special life stage [67–69], commuting mode [14,70,71], and availability of a private car [72–74], totaling 7 types of influencing factors. The various types of influencing factors were refined into specific indicators, as shown in Table 2.

**Table 2.** List of factors influencing the job–housing relationship, with TAZs as the unit of study.

Categories	Influencing Factors	Specific Indicators	Unit
Urban Built Environment Factors	Urban public transportation	Number and density of bus stations	pcs
	Compactness and scales	Density of resident population and workforce	persons/km <sup>2</sup>
	Mixed land use	Functional mixing degree	/
Personal Attributes Factors	Urban functional arrangement and industrial layout	Number and density of residential, medical, education and training, life service, exercise and fitness, cultural and media, government agency, corporate enterprise, financial, shopping, accommodation service, beauty, catering, tourist attractions, and leisure and entertainment POIs	POI number-pcs POI density-pcs/km <sup>2</sup>
	Income	Percentage of resident population and workforce with income of RMB 2499, RMB 2500–3999, RMB 4000–7999, RMB 8000–19,999, and RMB 20,000+	%
	Age	Percentage of resident population and workforce aged 18-, 18–24, 25–34, 35–44, 45–54, 55–64, and 65+	%
	Educational background	Percentage of resident population and workforce with educational background of upper secondary and below, associate degree, and bachelor’s degree and above	%
	Gender	Percentage of resident population and workforce whose sex is male or female	%
	Special life stages	Percentage of resident population and workforce at junior high school, attending high school, attending university, in postgraduate studies, pregnant, with a 0–1-year-old child at home, with a 1–3-year-old child at home, with a 3–6-year-old child at home, with primary school children at home, with junior high school students, with high school students, or with a pregnant woman	%
	Commuting mode	Percentage of resident population and workforce commuting by driving a car, by metro, by public transport, by bicycle, or on foot	%
	Availability of a private vehicle	Percentage of resident population and workforce with and without a private car	%

The degree of mixed land use was calculated with the help of Shannon's Diversity Index (SHDI) algorithm using POI data obtained from Baidu Map API [75]:

$$H = -\sum_{i=1}^N P_i \log_n P_i$$

where  $P_i$  represents the percentage of the  $i$ th POI and  $n$  represents the number of types [76].

### 3. Result

The population in the 435 TAZ research units was divided into resident population (people living in the unit) and working population (people working in the unit). The overall distribution of the resident and working populations is shown in Figure 3. The density distribution of the resident population showed a pattern of higher density in the periphery and lower density in the center. The residential population density in the TAZ units was mainly concentrated between 0.1 and 100,000 people per square kilometer, with significant variation. A river (Haihe River) runs through the center of Tianjin, with two districts on the east side and four districts on the west side. Along the Haihe River basin, the TAZs displayed a clear concentration of low residential population numbers and low population density. Regarding the working population, the density in the peripheral areas of the study region was significantly lower than in the central areas, forming a concentric pattern. In the central and southwestern parts of the study area, there is an inverse relationship between the indicators of working population density and population size. TAZs with high population density tended to have fewer workers, while TAZs with a larger working population tended to have a lower population density.

Then, the overall commuting flow is shown in Figure 4. In the figure, the lines and arrows represent the existence and direction of commuting relationships. The thinner and lighter the lines between points, the greater the number of commuters between two streets; conversely, thicker and darker lines indicate fewer commuters between two TAZs. The most obvious point is that due to the presence of a river in Tianjin's city center, we observed that the lines along both sides of the Haihe River and in the southern part of the study area were generally lighter and thinner. This indicates weaker commuting connections across the Haihe River, partly due to the relatively small populations within each TAZ, and partly because population movement within these TAZs does not have a strong directional focus. Then, the darker and thicker commuting lines on the eastern and western sides of the study area—representing internal connections on both sides of the Haihe River—indicate stronger connections. This analysis reveals the significant role that the Haihe River plays in dividing and obstructing urban transportation.

The quantified impact factors were fitted to the data on the one-way average commuting distances of both residents and the workforce to develop an impact model. The independent variables with significant effects, along with their mechanisms, are detailed in Appendices A and B. Because the names of the various variables were too long, the second column in the appendix is its abbreviation. The first two to three letters of the abbreviation represent the variables' keywords, the last letter represents the resident population (R) and the working population (W), and the lower right foot represents a more detailed classification, such as age and travel tools, etc.

Based on the  $R^2$  and significance values, of the above 12 influencing factors, it is clear that only 6 factors were significantly associated with the commuting distance of the residential population (Appendix A). There were 57 factors associated with the working population (Appendix B). Generally, the number and density of residents, the particular life stage they were in, the income of the labor force, the mode of commuting, and age had a stronger impact; the educational background of residents, the density of the labor force, and the city's functional distribution had a weaker relativity.





**Figure 3.** Heat map of the amount (left) and density (right) of the resident population (up) and working population (down) in the central area of Tianjin divided by TAZ units (the map is from Baidu Map Insight).

Based on the data results, in the correlation analysis of individual variables with the  $AOCD_R$  (average one-way commuting distance of resident population) and  $AOCD_W$  (average one-way commuting distance of the working population), a total of five variables showed a correlation with the  $AOCD_R$ . The 58 variables showed a correlation with the  $AOCD_W$ , and their correlations are shown in Table 3.

**Table 3.** Correlation of the individual variables with the  $AOCD_R$  and  $AOCD_W$ .

	Variable	Correlation
$AOCD_R$	PCR <sub>M</sub> (Percentage of resident population commuting by metro)	Positive
	NR (Number of resident population)	
	PCR <sub>W</sub> (Percentage of resident population commuting on foot)	Negative
	PCR <sub>B</sub> (Percentage of resident population commuting by bicycle)	
	PAR <sub>65+</sub> (Percentage of resident population aged 65+)	

Table 3. Cont.

	Variable	Correlation		
AOCD <sub>W</sub>	DW (Density of working population)	Positive		
	PIR <sub>2500–3999</sub> (Percentage of resident population with income of RMB 2500–3999)			
	PIR <sub>20,000+</sub> (Percentage of resident population with income of RMB 20,000+)			
	PIW <sub>2500–3999</sub> (Percentage of working population with income of RMB 2500–3999)			
	PIW <sub>8000–19,999</sub> (Percentage of resident population with income of RMB 8000–19,999)			
	PIW <sub>20,000+</sub> (Percentage of workforce with income of RMB 20,000+)			
	PAR <sub>18–24</sub> (Percentage of resident population aged 18–24)			
	PAW <sub>18–24</sub> (Percentage of workforce aged 18–24)			
	PAW <sub>25–34</sub> (Percentage of workforce aged 25–34)			
	PEBR <sub>H–</sub> (Percentage of resident population with an educational background of upper secondary and below)			
	PEBR <sub>B+</sub> (Percentage of resident population with educational attainment of a bachelor’s degree and above)			
	PSR <sub>M</sub> (Percentage of resident population male workforce)			
	PSW <sub>M</sub> (Percentage of working population male workforce)			
	PWB <sub>D</sub> (Percentage of workforce attending university)			
	PRM <sub>D</sub> (Percentage of workforce in postgraduate studies)			
	PR <sub>PH</sub> (Percentage of resident population with primary school children at home)			
	PW <sub>1–3CH</sub> (Percentage of workforce with a 1–3-year-old child at home)			
	PW <sub>3–6CH</sub> (Percentage of workforce with a 3–6-year-old child at home)			
	PW <sub>PH</sub> (Percentage of workforce with a pregnant woman at home)			
	PCR <sub>C</sub> (Percentage of resident population using a car as a mode of commuting)			
	PCW <sub>M</sub> (Percentage of workforce commuting by metro)			
			DR (Density of resident population)	Negative
			NR (Number of resident population)	
			N <sub>RPOI</sub> (Number of residential POIs)	
D <sub>RPOI</sub> (Density of residential POIs)				
N <sub>MPOI</sub> (Number of medical POIs)				
N <sub>BPOI</sub> (Number of beauty POIs)				
N <sub>LEPOI</sub> (Number of leisure and entertainment POIs)				
PIW <sub>2499–</sub> (Percentage of workforce with income of RMB 2499 or less)				
PAR <sub>35–44</sub> (Percentage of resident population aged 35–44)				
PAR <sub>55–64</sub> (Percentage of resident population aged 55–64)				
PAR <sub>65+</sub> (Percentage of resident population with income of 65+)				
PAW <sub>45–54</sub> (Percentage of workforce with income of 45–54)				
PAW <sub>55–64</sub> (Percentage of workforce with income of 55–64)				
PAW <sub>65+</sub> (Percentage of resident population with income of 65+)				
PEBR <sub>A</sub> (Percentage of resident population with an associate degree)				
PSR <sub>F</sub> (Percentage of females in the resident population)				
PSW <sub>F</sub> (Percentage of females in the workforce)				
PWM <sub>D</sub> (Percentage of workforce in postgraduate studies)				
PR <sub>1–3CH</sub> (Percentage of resident population with a 1–3-year-old child at home)				
PR <sub>3–6CH</sub> (Percentage of resident population with a 3–6-year-old child at home)				
PR <sub>PH</sub> (Percentage of resident population with primary school children at home)				
PW <sub>JHH</sub> (Percentage of workforce with junior high school students at home)				
PW <sub>HH</sub> (Percentage of workforce with high school students at home)				
PCW <sub>P</sub> (Percentage of workforce commuting by public transport)				
PCR <sub>P</sub> (Percentage of resident population commuting by public transport)				
PCR <sub>B</sub> (Percentage of resident population commuting by bicycle)				
PCR <sub>W</sub> (Percentage of resident population commuting on foot)				
PWCW <sub>N</sub> (Percentage of workforce without a private car)				

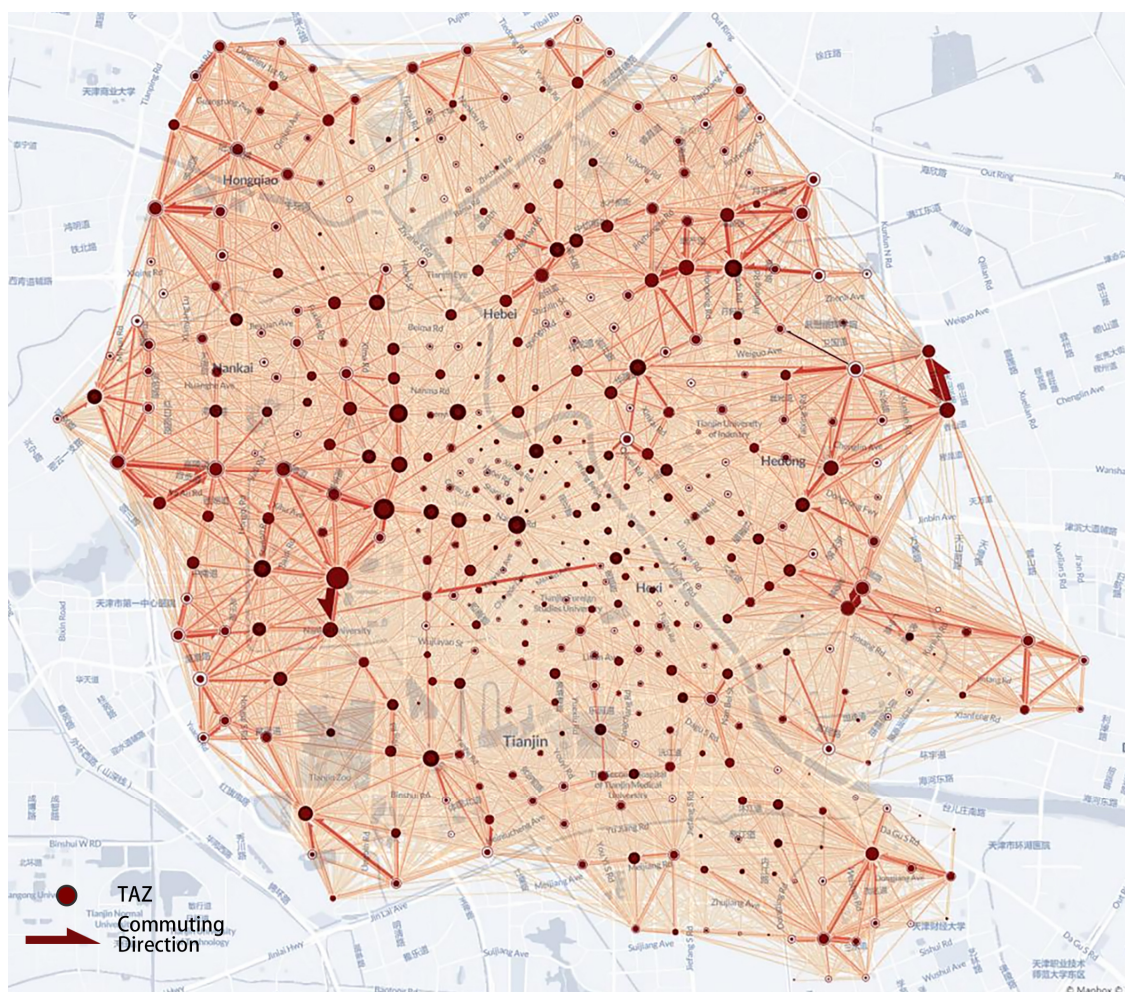


Figure 4. OD map of commuting in central area (the base map is from Baidu Map Insight).

### 3.1. Personal Attributes Factors

- Special life stage

$PW_{1-3CH}$  and  $PW_{3-6CH}$  were positively correlated with the  $AOCD_W$ ;  $PW_{JHH}$  and  $PW_{HH}$  were negatively correlated with the  $AOCD_W$ .

In the group that had already given birth, the mechanism of its  $AOCD_W$  was influenced by a three-way combination of school enrollment policies, the child's ability to commute independently to and from school, and the pursuit of quality educational resources. Although Tianjin holds the principle of relative proximity in kindergarten enrollment, only the type of enrollment "where the PRC household register and the house property certificate belong to the same place" can basically guarantee proximity to a kindergarten. In the other two types of enrollment, parents may choose a kindergarten farther away for better educational resources [77]. This leads to corresponding policies that have less control over commuting distances for families with young children. Therefore, narrowing the differences in the teaching quality among schools would effectively reduce the long-distance commuting generated by school choice. For primary and junior high school students, on the one hand, the local government mainly adopts the registration or peer-to-peer approach, and thus most of them are enrolled in schools in their vicinity. On the other hand, high school students are already capable of accomplishing short-distance commuting to and from school on their own, while primary school students in lower grades do not have the ability to achieve this yet. The policy effectively saves parents' commuting distances. At present, since it is difficult to quantify the strength of the impact of this policy and many data are in a state of secrecy, most of the existing research on the impact of the policy is qualitative

research, with and few quantitative studies, which is not conducive to the study of the relevant theoretical basis.

As for the positive effect of the percentage of undergraduate and graduate students on the  $AOCD_W$ , it can be explained in two ways. (1) Due to the accommodation system of Chinese universities, areas with a higher  $PW_{BD}$  can basically be recognized as the universities and their surroundings. Although students have shorter commuting distances, college campuses typically have a larger floor area and do not allow for outside vehicle traffic, so detours result in an increased  $AOCD_W$ . (2) College students classified as labor force are often in the internship stage, and they usually give more priority to factors related to their own development rather than commuting distance in their job choices.

- Age

There is a clear hierarchical pattern in the effect of age on commuting distance. For both residents and the workforce, the percentage of the population in the 18–34 age group was positively correlated with the  $AOCD_W$ ; the percentage of the population in the 35+ age group, especially the 55+ age group, was negatively correlated with the  $AOCD_W$ .

This is due to the fact that the emphasis of life is different for each age group, but pursuits are similar for the same age group. The 18–34 range is the age when people are just starting to become employed and put together a career. They are often willing to take on longer commutes for better job opportunities. The 35–54 age group is relatively better able to work or is in a more stable employment relationship. This generally means that they are financially capable and hence have more control over their employment and residential space choices. The 55–64 age group is inversely related to commuting distances, as they are around the retirement age with stable jobs and much less need to transport children at home. This also verifies the reason why the commuting behavior of the central area was significantly weaker than that in the surrounding areas.

In China, most urban residents over the age of 65 are retired and do not need to participate in commuting. There are three possibilities for their commuting behavior. (1) They could still be involved in commuting for reasons such as being rehired by their original organization; similar phenomena are mostly found in hospitals and schools, combined with the specifics of the study area, where the work unit is likely to have established a family zone in the planned economy and retained it to today, e.g., rehired professors and staff at Tianjin University and Nankai University, with a shorter commuting distance. (2) They could participate in commuting by transporting grandchildren to and from school; most families do not bother the elderly with long-distance transportation due to their physical state, which saves commuting distances for the parents of the children but increases the amount of commuting. (3) Trips for daily activities such as walking, grocery shopping, and buying breakfast were recorded as commuting, mainly around residences and over short distances.

- Gender

Whether it was residents or the workforce, the male population percentage was positively correlated with the  $AOCD_W$ , while the female population percentage was negatively correlated with it. Arguably, gender had a significant effect at the study level of the TAZ.

The main reasons are categorized into the following three areas: (1) under the influence of the traditional Chinese idea that “men are responsible for working hard and women are expected to take charge of household affairs”, women prefer to keep their workplaces closer to their homes in order to take care of their families; (2) when choosing a place of residence after both spouses have regular jobs, the man often chooses to live closer to the woman’s employment place out of concern for the woman; and (3) where couples share a car, men tend to be the primary users, which increases men’s tolerance for long-distance commuting.

In terms of reducing overall commuting distances, interventions can be made by installing more jobs targeting female recruitment in and around residential areas. From another perspective, such an approach may aggravate the shackles of the ideology that “women should emphasize taking care of their families rather than their careers”, hindering



women's progress towards independence and autonomy and aggravating gender antagonism. This also indicates that holistic consideration should be given to upholding fairness and justice for all parties when formulating relevant policies.

- Educational background

$PEBR_H$  and  $PEBR_{B+}$  were positively correlated with the  $AOCD_W$ , and  $PEBR_A$  was negatively correlated with it.

Educational background influences employment and residential choices to a considerable extent, thus leading to differences in the mechanisms by which commuting distances are affected by different educational qualifications. Most of the job opportunities available to the group with high school education and below are dominated by low-skilled, low-knowledge, heavy manual labor. Such jobs are more likely to be clustered in urban centers and are characterized by low stability. High housing prices force some of the less educated to live in suburban areas and endure long commutes. Part of the low-educated are willing to put up with the dilapidated environment of shantytowns or urban villages in the central city in order to maintain a convenient, low-cost commute. With higher education, people are faced with richer employment opportunities, and considerations of their career prospects outweigh the desire to commute short distances. A bachelor's degree or higher thus contributes to long-distance commuting. The higher the number of residents who commute long distances, the smaller the proportion of in-place employment within the region, and the commuting distance of the labor force increases as a result.

- Income

The mechanism of the effect of income on commuting distance formed a dividing line at a monthly income of RMB 2500:  $PIR_{2499-}$  and  $PIW_{2499-}$  were both negatively correlated with the  $AOCD_W$ ;  $PIR_{2500-3999}$ ,  $PIW_{2500-3999}$ ,  $PIW_{8000-19,999}$ ,  $PIR_{20,000+}$ , and  $PIW_{20,000+}$  were positively correlated with it.

For the group with a monthly income of less than RMB 2499, constrained by the cost of commuting and salary levels, they have lower demands regarding quality of life. Living in urban villages can combine low rents and low transportation costs with nearby employment and a better match between work and residential space. Higher-income groups are more capable of choosing jobs, choosing where to live, and affording commuting costs. Higher incomes mean that the corresponding groups have higher requirements in terms of living quality and living conditions. They try to avoid settling in old urban areas dominated by a large number of old, neglected, and unrepaired residential neighborhoods with high housing prices, which constitutes long-distance commuting and raises the  $AOCD_W$ . Thus, while many job-housing studies have focused more on low-income groups, which are more sensitive to changes in commuting costs, the positive impact of middle- and high-income groups on commuting distances should not be underestimated.

- Commuting mode

$PCR_C$  and  $PCW_M$  were positively correlated with the  $AOCD_W$ ;  $PCR_M$  was positively correlated with the  $AOCD_R$ .  $PCW_P$ ,  $PCR_P$ ,  $PCR_B$ , and  $PCR_W$  were negatively correlated with the  $AOCD_W$ , where  $PCR_B$  and  $PCR_W$  were also negatively correlated with the  $AOCD_R$ . These patterns can be basically summarized as follows: among the effects of commuting modes on commuting distances, driving and taking the subway were positively correlated with it, while in terms of taking public transportation, cycling and walking were negatively correlated with it.

There are two main reasons for the positive correlation between the percentage of people commuting by car and commuting distance. On the one hand, owing to the fact that commuting in a private car is less affected by weather and other factors, offering greater stability and faster driving speeds, driving will greatly increase people's tolerance for long commutes. On the other hand, the larger the proportion of people commuting by car, the higher the traffic volume within each study unit. The lack of parking space for private cars and lazy management have led to a serious problem of on-street parking in the study area.



Situations such as detours due to traffic congestion are more likely to occur, thus lengthening commuting distances. The two aspects reinforce each other. Relying on its convenient, fast, and inexpensive characteristics, subway commuting has expanded the range of tolerable commuting distances for citizens. Typically, cycling, walking, and public transportation are suitable for shorter distances. Therefore, the percentage of people choosing these types of commuting is equivalent to the percentage of short distances commuted.

- Availability of a private car

$PWCR_Y$  was positively correlated with the  $AOCD_R$ , and  $PWCW_N$  was negatively correlated with the  $AOCD_W$ . The reasons for this phenomenon are consistent with the use of driving as a mode of commuting. It is evident that controlling car ownership and strengthening traffic regulation should be an effective way to shorten the commuting distance.

### 3.2. Urban Built Environment Factors

- Compactness and scales

NR was directly proportional to the  $AOCD_R$ ; NR and DR were inversely proportional to the  $AOCD_W$ , and DW was directly proportional to the  $AOCD_W$ . Area size had no significant effect on commuting distance.

The higher the values of NR and DR in the same region, the richer the demand, and more jobs ensue. The feasibility and likelihood of residents working close to their homes are subsequently increased. The higher the DW, the less living space there is in the area; therefore, land prices and house prices are likely to rise due to employment agglomeration. The combination of the two factors brings about a trade-off between the cost of commuting and housing. As it is more affordable, enduring a long commute becomes an option for most people. However, overly compact settlements and a large number of inhabitants make the supply of jobs outstrip the demand and eventually orient to extreme areas of mono-functionality, as exemplified by Tiantongyuan in Beijing.

Combining the regression results, theoretical extrapolations, and the actual situation led to the determination that the positive and negative relationship of population density was within certain limits. The linear law derived in this study may be due to the fact that the established fitted data were mainly distributed in the positively or negatively correlated segments of the overall law; in addition, cities are at different developmental stages, which proves that the study of job–housing relationships is site-specific. Therefore, from the perspective of urban planning, the relevant government departments should strengthen the detailed control and balanced matching of land function planning and corresponding data indicators such as the floor area ratio so as to avoid the emergence of extreme situations in which the scale and density of the population are too high or too low at the source.

- Urban public transportation

With TAZs as the study unit,  $N_{BS}$  and  $D_{BS}$  had no significant effect on the  $AOCD_R$  and  $AOCD_W$ . This was probably due to the large difference in the scale of the TAZ compared to the range of public transportation services, which makes it difficult to represent at the TAZ level.

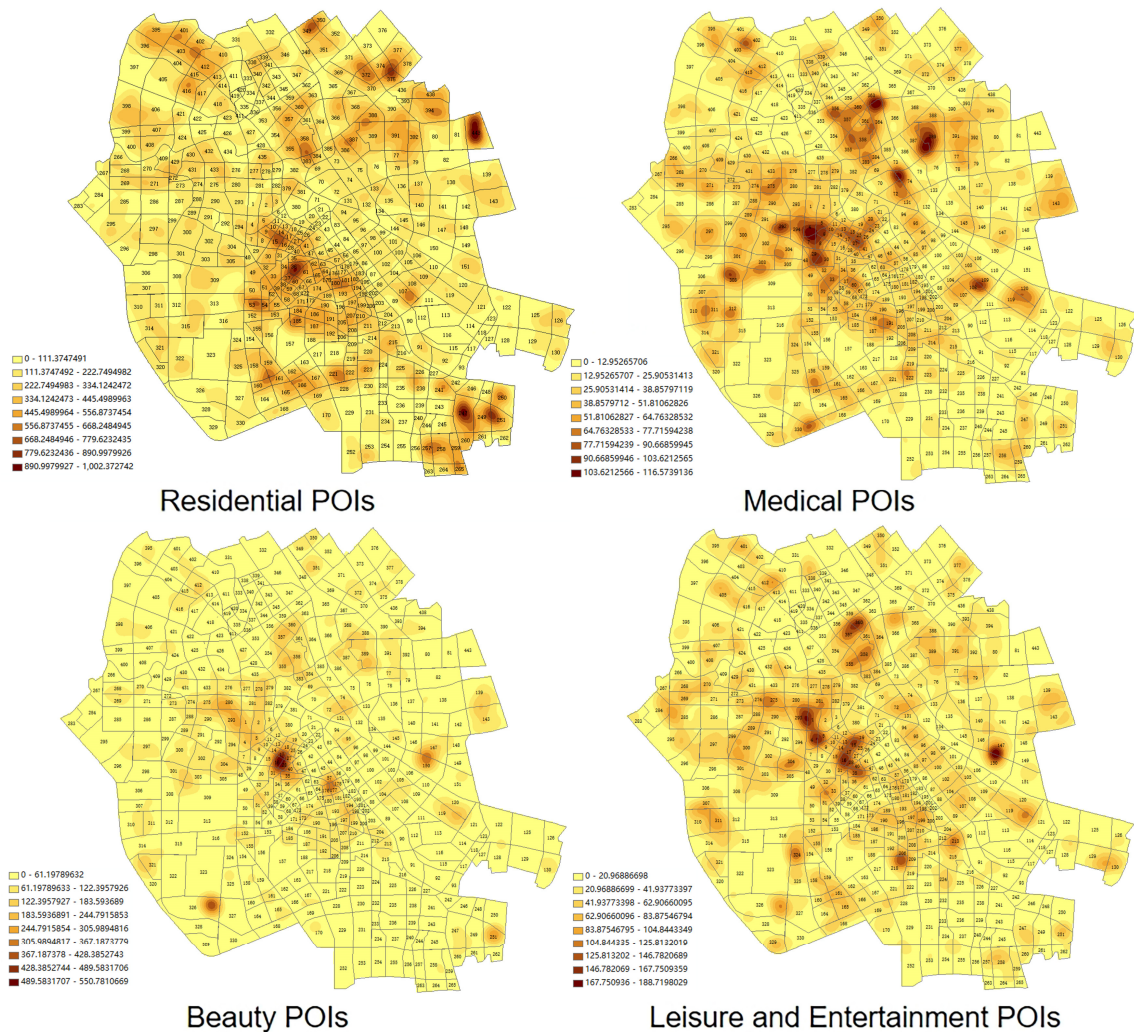
- Mixed land use

Functional mixing had no significant effect on commuting distance with the TAZ as the unit of study, which is generally consistent with established research findings. This is related to the size of the study unit on the one hand, and on the other hand, the degree of functional mixing may work mainly in conjunction with other factors and weakly on its own.

- Urban functional arrangement

$NR_{RPOI}$ ,  $DR_{RPOI}$ ,  $N_{MPOI}$ ,  $N_{BPOI}$ , and  $N_{LEPOI}$  were all inversely proportional to the  $AOCD_W$ . In the same way as NR and DR, the higher the number and density of residential POIs, the more likely they are to produce residential agglomerations, the more likely they are

to provide residential possibilities for the nearby working population, and the shorter the  $AOCD_W$ . The kernel density analysis of each type of POI point by Arcgis (10.5) is shown in Figure 5. It was found that the POI categories of beauty, leisure and entertainment, and medical had commonality in terms of site selection. Medical POIs were mainly located in residential agglomerations, and most of the other two types of POIs were located in commercial or residential agglomerations to achieve the purpose of attracting patronage and creating opportunities for employment in the vicinity, leading to a shorter  $AOCD_W$ .



**Figure 5.** Kernel density analysis of POIs with significant effect on  $AOCD_W$  (the base map is from Baidu Map Insight).

#### 4. Conclusions

This study investigated the influencing factors of the job–housing relationship and its influencing mechanisms in the central urban area of Tianjin with the TAZ as the research unit, compounding the built environment factors and personal attributes factors. The results show the following:

- (1) The river in Tianjin has a significant impact on the commuting preferences of the urban population. The distribution of both the resident and working populations in each TAZ unit is centered around the Haihe River, showing a concentric pattern.
- (2) Both personal attribute factors and urban built environment factors have an impact on the job–housing relationship, while personal attribute factors have a stronger impact. For example, the proportion of the population under the age of 35 is positively

correlated with the average commuting distance, while the proportion of those over 65, most of whom are retired, is negatively correlated with the average commuting distance. Similarly, in terms of income, the proportions of both low-income and high-income groups are negatively correlated with commuting distance.

- (3) All types of influences related to the working population have a weaker impact on the average one-way commuting distance of the resident population ( $AOCD_R$ ), and the average one-way commuting distance of the working population ( $AOCD_W$ ) is more sensitive to both resident and working population factors.
- (4) The significant impact of most factors actually stems from joint effects with other factors, such as the joint effect of special life stages with local school enrollment policies and the quality of teaching and learning in different regions or the joint effect of gender factors with traditional Chinese gender concepts.

This research provides a direct theoretical basis for the optimization of the urban occupational and residential spatial structure and a sample for the improvement of the database for job–housing studies, with a view to enabling relevant studies to advance from the monitoring stage to simulation.

## 5. Discussion

In linear regression analysis, while an  $R^2$  value greater than 0.5 is generally considered valid, an  $R^2$  exceeding 0.7 is typically deemed significant in practice. According to the  $R^2$  values presented in Appendices A and B, the overall fit of the influencing factors was moderate, with only five variables surpassing the 0.7 threshold. These five variables were negatively correlated with commuting distance among the working population within the TAZ units: the percentage of the workforce commuting by bicycle ( $PCW_B$ ), the percentage commuting on foot ( $PCW_W$ ), the percentage of the workforce with an age of 65+ ( $PAW_{65+}$ ), the percentage of the resident population with an associate degree ( $PEBR_A$ ), and the percentage of females in the workforce ( $PSW_F$ ). So, strictly speaking, only these five factors can confirm a clear correlation with commuting distance, and the validity of the other factors needs to be further verified.

This finding underscores the intricacy of social factors that influence commuting distances, and the variables examined in this study constitute merely a subset of the overarching equation. The precise integration of big data with personal information to statistically delineate travel purposes and commuting modes is currently fraught with challenges. These challenges can introduce biases into the outcomes of quantitative research. For instance, the proliferation of shared bicycles in China has led to a potential misclassification of some individuals as cyclists. They may use bicycles only for the segment of their journey between subway stations and their homes, rather than for the entire commute. Consequently, the extent to which cycling commuting is significantly associated with short-distance commuting is a question that merits further exploration.

Future research should focus more intently on the synergistic effects of multiple factors, closely monitor data trends, and deepen the understanding of the interplay between employment and housing. Commuting distance is also intricately connected to non-quantifiable elements, such as local lifestyle habits and prevailing policies. At the urban micro-level, factors such as school enrollment policies, the quality of education, and work modalities in knowledge-intensive industries may be amenable to short-term adjustments. In contrast, variables like the population's age structure, educational distribution, urban functional zoning, and the prevalence of private vehicles necessitate longer periods for recalibration. Consequently, optimization strategies must embrace a multi-faceted and incremental approach. These strategies should include stringent transportation regulations, adaptive guidance for spatial transformations, proactive advocacy through media campaigns and educational programs, and robust legislative and policy frameworks. Such a holistic approach can provide the essential support and impetus for reestablishing the urban job–housing equilibrium, ultimately fostering a virtuous cycle that aims for self-sufficiency and balanced supply-and-demand dynamics.

Furthermore, to achieve a sustainable equilibrium between urban employment and residential land use, it is imperative to advance research on employment–housing relationships using data that exhibit temporal continuity, thereby enabling the formulation of more targeted solutions in future studies. Indeed, most current data-driven research adheres to a developmental trajectory of “simulation”–“monitoring”–“analysis”–“prediction”. Presently, our understanding of the evolving relationship between work and residence remains in the nascent stages of “simulation” and “monitoring”, which involves striving to objectively replicate and observe the most recent temporal snapshot through data. This has resulted in the majority of existing research recommendations being nonspecific and in need of enhanced operational clarity. Data with temporal continuity can be instrumental in refining simulation models, regulating based on empirical observations, and subsequently facilitating analysis and prediction.

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**Data Availability Statement:** The data presented in this study are available in Baidu Huiyan at [https://e.baidu.com/lp/lpapply6/?refer=113094195&bd\\_vid=8624833336874606140](https://e.baidu.com/lp/lpapply6/?refer=113094195&bd_vid=8624833336874606140), accessed on 1 July 2024.

**Conflicts of Interest:** The authors declare no conflicts of interest.

## Appendix A

**Table A1.** TAZ level: linear regression with average one-way commuting distance (AOCD<sub>R</sub>) of resident population as dependent variable.

Independent Variable	Acronym	F	R <sup>2</sup>	Significance	Equation
Positive Correlation					
Percentage of resident population commuting by metro	PCR <sub>M</sub>	16.871	0.538	0.000	$y = 3.549 + 0.242x$
Percentage of resident population with a private car	PWCR <sub>Y</sub>	4.221	0.510	0.041	$y = 6.841 + 0.075x$
Number of people in resident population	NR	5.474	0.512	0.020	$y = 8.614 + (7.219 \times 10^{-5})x$
Negative Correlation					
Percentage of resident population commuting on foot	PCR <sub>W</sub>	24.358	0.553	0.000	$y = 13.270 - 0.673x$
Percentage of resident population commuting by bicycle	PCR <sub>B</sub>	22.859	0.550	0.000	$y = 16.602 - 0.417x$
Percentage of resident population aged 65+	PAR <sub>65+</sub>	4.368	0.510	0.037	$y = 10.520 - 0.220x$

## Appendix B

**Table A2.** TAZ level: linear regression with average one-way commuting distance of working population ( $AOCD_W$ ) as dependent variable.

Independent Variable	Acronym	F	R <sup>2</sup>	Significance	Equation
Positive Correlation					
Percentage of resident population in postgraduate studies	PR <sub>MD</sub>	6.141	0.514	0.014	$y = 8.154 + 0.303x$
Percentage of workforce with an income of RMB 2500–3999	PIW <sub>2500–3999</sub>	11.257	0.525	0.001	$y = 7.094 + 0.187x$
Percentage of workforce with an income of RMB 20,000+	PIW <sub>20,000+</sub>	48.593	0.601	0.000	$y = 6.843 + 0.183x$
Percentage of workforce with a pregnant woman at home	PW <sub>PH</sub>	8.424	0.519	0.004	$y = 7.621 + 0.163x$
Percentage of workforce with a 3–6-year-old child at home	PW <sub>3–6CH</sub>	50.488	0.604	0.000	$y = 6.486 + 0.153x$
Percentage of workforce with a 1–3-year-old child at home	PW <sub>1–3CH</sub>	15.128	0.534	0.000	$y = 7.289 + 0.149x$
Percentage of workforce commuting by metro	PCW <sub>M</sub>	98.243	0.685	0.000	$y = 5.208 + 0.128x$
Percentage of resident population with an income of RMB 2500–3999	PIR <sub>2500–3999</sub>	6.388	0.515	0.012	$y = 7.537 + 0.126x$
Percentage of resident population using a car as a mode of commuting	PCR <sub>C</sub>	12.132	0.527	0.001	$y = 6.165 + 0.115x$
Percentage of workforce aged 25–34	PAW <sub>25–34</sub>	57.882	0.618	0.000	$y = 4.779 + 0.104x$
Percentage of workforce aged 18–24	PAW <sub>18–24</sub>	46.971	0.598	0.000	$y = 7.653 + 0.104x$
Percentage of workforce with an income of RMB 8000–19,999	PIW <sub>8000–19,999</sub>	65.876	0.632	0.000	$y = 6.596 + 0.102x$
Percentage of workforce whose sex is male	PSW <sub>M</sub>	36.893	0.579	0.000	$y = 2.638 + 0.088x$
Percentage of resident population with an income of RMB 20,000+	PIR <sub>20,000+</sub>	9.896	0.522	0.002	$y = 7.646 + 0.082x$
Percentage of resident population whose sex is male	PSR <sub>M</sub>	35.319	0.575	0.000	$y = 3.271 + 0.076x$
Percentage of resident population aged 18–24	PAR <sub>18–24</sub>	22.413	0.549	0.000	$y = 7.812 + 0.075x$
Percentage of workforce attending university	PWB <sub>D</sub>	35.448	0.576	0.000	$y = 7.806 + 0.060x$
Percentage of workforce with a private car	PWCW <sub>Y</sub>	34.907	0.575	0.000	$y = 5.804 + 0.058x$
Percentage of resident population with an income of RMB 8000–19,999	PIR <sub>8000–19,999</sub>	9.534	0.522	0.002	$y = 7.461 + 0.057x$
Percentage of workforce with educational attainment of a bachelor's degree and above	PEBW <sub>B+</sub>	38.939	0.583	0.000	$y = 7.092 + 0.55x$
Percentage of resident population aged 25–34	PAR <sub>25–34</sub>	11.389	0.526	0.001	$y = 6.710 + 0.045x$
Percentage of resident population attending university	PR <sub>BD</sub>	15.274	0.534	0.000	$y = 7.933 + 0.038x$
Percentage of resident population with educational background of upper secondary and below	PEBR <sub>H-</sub>	14.405	0.532	0.000	$y = 6.437 + 0.034x$
Percentage of resident population with educational attainment of a bachelor's degree and above	PEBR <sub>B+</sub>	5.864	0.513	0.016	$y = 7.714 + 0.031x$
Density of working population	DW	4.820	0.511	0.029	$y = 8.027 + (1.237 \times 10^{-5})x$
Negative Correlation					
Density of resident population	DR	8.187	0.519	0.004b	$y = 8.461 - (9.400 \times 10^6)x$
Number of people in resident population	NR	32.909	0.571	0.000b	$y = 8.744 - (6.254 \times 10^5)x$
Percentage of workforce commuting by bicycle	PCW <sub>B</sub>	309.948	0.917	0.000	$y = 17.406 - 0.528x$
Percentage of workforce commuting on foot	PCW <sub>W</sub>	186.282	0.801	0.000	$y = 10.773 - 0.457x$
Percentage of workforce with an age of 65+	PAW <sub>65+</sub>	136.162	0.739	0.000	$y = 9.862 - 0.440x$
Percentage of workforce in postgraduate studies	PWM <sub>D</sub>	5.702	0.513	0.017	$y = 8.156 - 0.298x$
Percentage of workforce with an age of 55–64	PAW <sub>55–64</sub>	136.616	0.740	0.000	$y = 10.743 - 0.227x$



Table A2. Cont.

Independent Variable	Acronym	F	R <sup>2</sup>	Significance	Equation
Percentage of resident population with an age of 65+	PAR <sub>65+</sub>	27.215	0.659	0.000	$y = 9.356 - 0.195x$
Percentage of resident population with an age of 55–64	PAR <sub>55–64</sub>	57.087	0.616	0.000	$y = 10.475 - 0.191x$
Percentage of resident population with a 0–1-year-old child at home	PR <sub>0–1CH</sub>	10.777	0.524	0.001	$y = 9.093 - 0.183x$
Percentage of workforce with high school students at home	PW <sub>HH</sub>	24.685	0.554	0.000	$y = 9.520 - 0.169x$
Percentage of workforce with junior high school students at home	PW <sub>JHH</sub>	52.486	0.608	0.000	$y = 10.095 - 0.163x$
Percentage of resident population with a 1–3-year-old child at home	PR <sub>1–3CH</sub>	10.777	0.524	0.001	$y = 8.969 - 0.162x$
Percentage of resident population with an associate degree	PEBR <sub>A</sub>	122.280	0.720	0.000	$y = 12.634 - 0.142x$
Percentage of workforce with an income of RMB 2499 or less	PIW <sub>2499–</sub>	103.772	0.693	0.000	$y = 11.737 - 0.111x$
Percentage of females in the resident population	PSR <sub>F</sub>	53.515	0.610	0.000	$y = 11.417 - 0.092x$
Percentage of females in the workforce	PSW <sub>F</sub>	33.536	0.920	0.000	$y = 11.195 - 0.081x$
Percentage of resident population commuting by public transport	PCR <sub>P</sub>	10.011	0.523	0.002	$y = 11.007 - 0.080x$
Percentage of resident population aged 35–44	PAR <sub>35–44</sub>	18.767	0.542	0.000	$y = 10.213 - 0.074x$
Percentage of resident population with a 3–6-year-old child at home	PR <sub>3–6CH</sub>	4.946	0.511	0.027	$y = 8.823 - 0.074x$
Percentage of resident population with an income of RMB 2499 or less	PIR <sub>2499–</sub>	30.717	0.566	0.000	$y = 10.402 - 0.066x$
Percentage of workforce without a private car	PWCW <sub>N</sub>	38.068	0.581	0.000	$y = 11.909 - 0.063x$
Percentage of workforce aged 45–54	PAW <sub>45–54</sub>	4.247	0.510	0.040	$y = 9.184 - 0.059x$
Percentage of workforce commuting by public transport	PCW <sub>P</sub>	4.239	0.510	0.040	$y = 10.229 - 0.056x$
Percentage of workforce with primary school children at home	PW <sub>PH</sub>	19.176	0.542	0.000	$y = 9.813 - 0.043x$
Percentage of workforce with an income of RMB 4000–7999	PIW <sub>4000–7999</sub>	4.255	0.510	0.040	$y = 9.608 - 0.036x$
Percentage of resident population with primary school children at home	PR <sub>PH</sub>	7.475	0.517	0.007	$y = 9.531 - 0.032x$
Number of medical POIs	N <sub>MPOI</sub>	10.931	0.525	0.001	$y = 8.468 - 0.028x$
Number of leisure and entertainment POIs	N <sub>LEPOI</sub>	7.670	0.517	0.006	$y = 8.417 - 0.017x$
Number of beauty POIs	N <sub>BPOI</sub>	4.330	0.510	0.038	$y = 8.362 - 0.008x$
Number of residential POIs	N <sub>RPOI</sub>	20.909	0.546	0.000	$y = 8.598 - 0.005x$
Density of residential POIs	DR <sub>POI</sub>	8.672	0.520	0.003	$y = 8.501 - 0.001x$

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