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Analysis of Jobs-Housing Relationship and Commuting Characteristics Around Urban Rail Transit Stations

TONGFEI LI[1], YANYAN CHEN[1], ZHEN WANG[2], ZHUO LIU[1], RUI DING[3], (Member, IEEE), AND SHUQI XUE[4]

[1]Beijing Key Laboratory of Traffic Engineering, Beijing University of Technology, Beijing 100124, China
[2]Qingdao City Planning and Design Institute, Qingdao 266071, China
[3]College of Big Data Application and Economics, Guizhou University of Finance and Economics, Guiyang 550025, China
[4]School of Modern Posts, Xi'an University of Posts and Telecommunications, Xi'an 710061, China

Corresponding author: Rui Ding (396124877@qq.com)

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ABSTRACT In recent years, with the acceleration of the urbanization process, the contradiction between transportation infrastructure facilities and spatial layout of urban land use is escalating. However, integrated urban planning and transportation planning provides a new way to significantly relieve traffic congestion and the phenomenon of jobs-housing separation brought by urbanization. In this study, the massive internet data of urban planning (e.g. internet-based positioning data) and traditional data resources of the traffic system (e.g. smart card data) are combined to identify the jobs-housing relationship around urban rail transit stations instead of the method of theoretical modeling. All the stations are classified into different categories on this basis. Besides, as for the connections of different regions and the spatial distribution of the urban population, the method of smart card data mining is adopted to analyze commuting characteristics and spatial distribution of origin-destination travel demand for different categories of stations. Finally, analysis of the correlation between the resident population around urban rail transit stations and commuting passenger flow is carried out by statistical methods. Corresponding results can be further applied to the integrated planning of transportation and land use.

INDEX TERMS Transportation, land use planning, jobs-housing relationship, urban areas, big data applications, commuting passenger.

I. INTRODUCTION

Integrated urban planning and transportation planning is the trend of development in the future [1]–[4]. Due to the character of high-carrying-capacity, low emission and high speed, the urban rail transit system has significant advantages in the mitigation of traffic congestion, integrated urban and transportation planning. For a better matching of urban rail transit planning and land use planning in the future, it is necessary to analyze the current jobs-housing relationship and commuting characteristics around urban rail transit stations. In our previous studies, we focus on the integrated transportation and land use problem from the perspective of theoretical modeling with hypothetical ideal scenarios and aim to provide a co-evolution model of land use and traffic network design [5], a general model for the formulation of residential location choice behavior [6], [7], optimization framework of urban transportation planning [8], [9] and management [10]. Besides, almost all the optimization model, the proposed transportation and land use equilibrium theory are derived under a complete market assumption.

Recently, the related studies on transportation and land use based on multi-source big data receive a lot of attention [11]–[14]. Du [15] proposed a method to recognize passengers' residential location and working location in the urban rail transit system based on the mobile phone signaling data. Then, for commuting passengers at each station, the transfer convenience between urban rail transit

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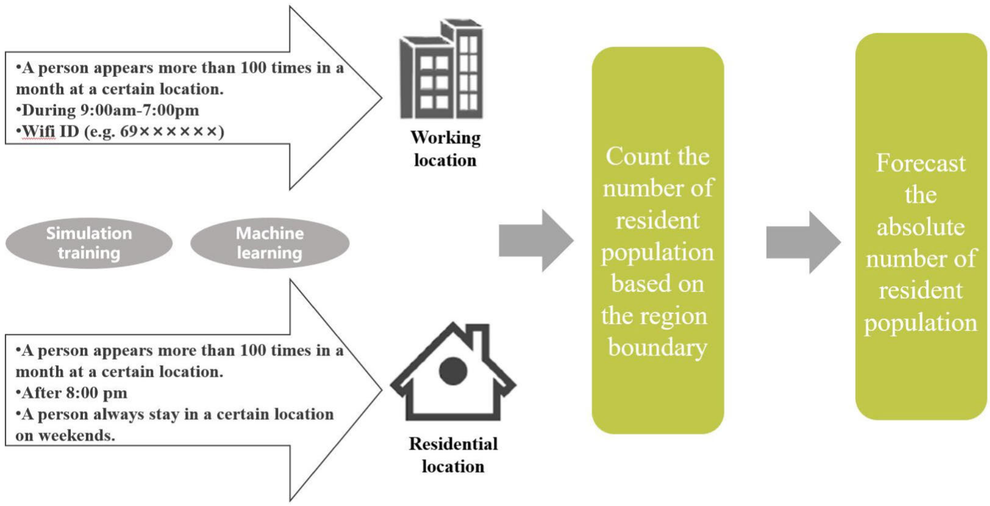

FIGURE 1. Forecast the number of resident population based on the location data.

and other traffic modes is analyzed. Based on the statistical data of Beijing urban rail transit, Dou *et al.* [16] analyzed the spatial distribution of commuting passenger flow during morning peak hours. Xu [17] analyzed the commuting characteristics and jobs-housing spatial distribution in Shanghai based on public transit data. Based on the smart card data, Shen [18] gave a multidimensional analysis of the relationship between commuting time and jobs-housing separation from the perspective of the whole city, city center, and suburbs. Except for the smart card data, other data resources were also adopted. Liu [19] studied the commuting characteristics and the jobs-housing spatial distribution in Wuhan based on the smart card data and Point-of-Interest (POI) data. Liu and Wang [20] calculated the employment accessibility of 124 streets in Beijing based on the commuting time, which is taken as the measurement index of jobs-housing separation. Besides, the relationship between jobs-housing separation and residents' commuting time was analyzed. Zhao *et al.* [21] adopted the questionnaire survey to collect the data of commuting and jobs-housing distribution along urban rail transit lines. Then, the effect of the urban rail transit system on the jobs-housing spatial distribution was analyzed.

Here, different from our previous work from the perspective of theoretical modeling with hypothetical ideal scenarios and other related studies based on single data source (e.g. smart card data, mobile phone signaling data, POI data, survey data), we aim to study the interrelationship between urban rail traffic system and land use based on the multi-source big data and make up for shortcomings of the theoretical modeling methods. Smart card data gathered by automated fare collection (AFC) systems and internet-based positioning data collected by various mobile apps are valuable resources for studying urban mobility. First, the massive internet data of urban planning (e.g. internet-based positioning data) and traditional data resources of the traffic system (e.g. smart card data) are combined to identify the jobs-housing relationship around urban rail transit stations. All the stations are classified into three different categories on this basis: living-oriented station, working-oriented station, station under jobs-housing balance. Second, as for the connections of different regions and the spatial distribution of the urban population, the method of smart card data mining is adopted to analyze commuting characteristics and spatial distribution of origin-destination travel demand for different categories of stations. Third, analysis of the correlation between the resident population around urban rail transit stations and commuting passenger flow is carried out by statistical methods. The case study of Qingdao city in China is used to demonstrate the properties of the problem.

The rest of this paper is organized as follows. In the next section, the jobs-housing relationship around urban rail transit stations is analyzed. In Section 3, commuting passengers are identified from all passengers. Besides, their commuting characteristics in different stations and the distribution of OD commuting demand are analyzed. Correlation analysis between the resident population around the station and commuting passenger flow is given in Section 4. Section 5 provides some concluding remarks.

II. ANALYSIS OF JOBS-HOUSING RELATIONSHIP AROUND URBAN RAIL TRANSIT STATIONS

A. DISTRIBUTION OF POPULATION AND JOBS

In September 2017, Qingdao City Planning and Design Institute union with Baidu Map Huiyan establish the Joint Innovation Lab of Baidu Huiyan and Qingdao Planning. It is dedicated to applying the big data and technology of artificial intelligence to regional and urban planning, urban transportation planning and consulting. Based on the massive location data of various apps that rely on the location-based service (LBS) supported by Baidu, the resident population and working population of each region can be calculated through the method of model training and machine learning as shown in Figure 1. The prediction accuracy rate can reach up to 85%.

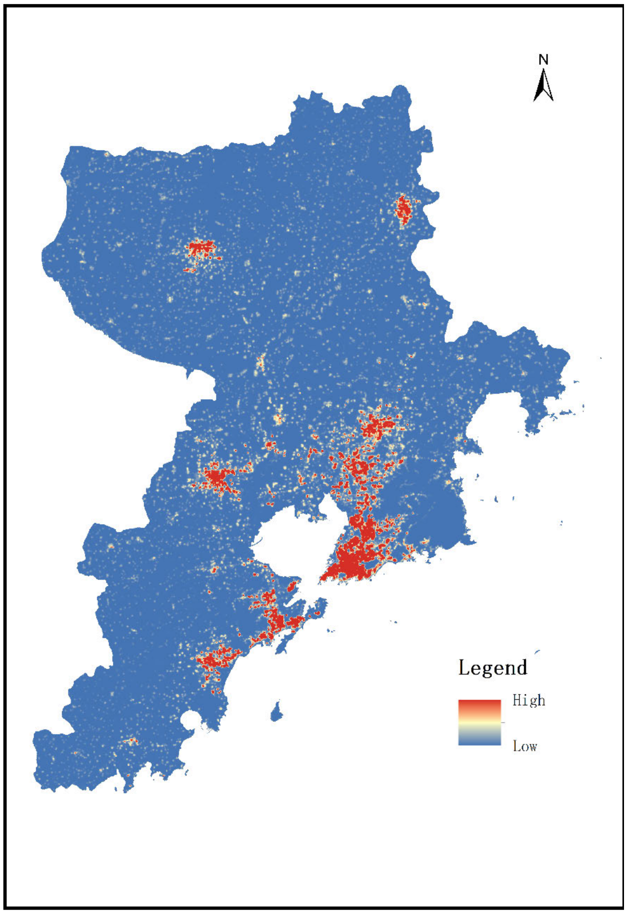

FIGURE 2. The spatial distribution of resident population in Qingdao.

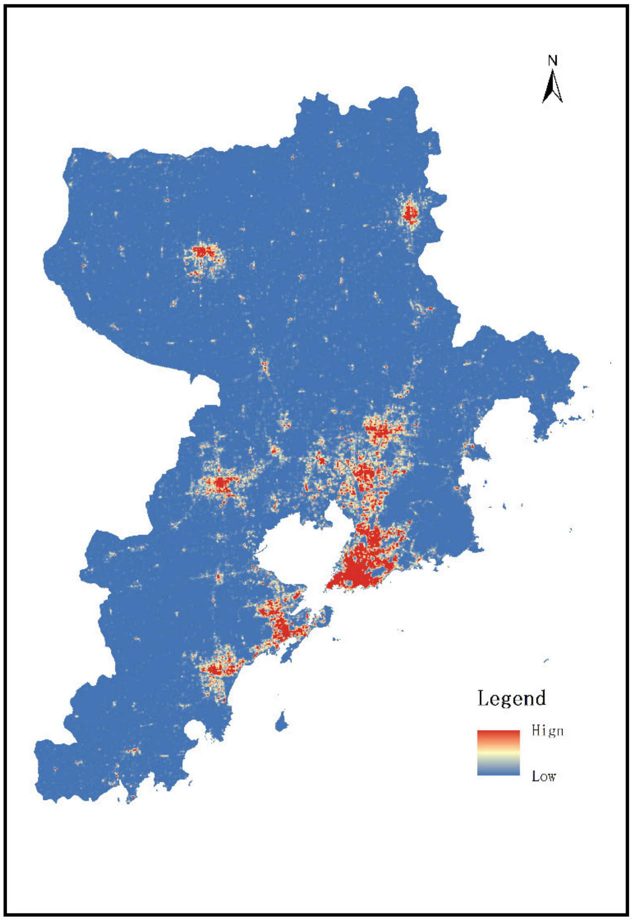

FIGURE 3. The spatial distribution of jobs in Qingdao.

In this subsection, after dividing the city into squared grids ($50m \times 50m$), we can use the space connection function of ArcGIS to count the resident and working population in each area.

Based on the above work, it is found that the resident population in Qingdao is 10.55 million by 2018, while the number of jobs is 4.03 million. The ratio of the resident population to the number of jobs is 0.38. Using the kernel density of ArcGIS, we can obtain the spatial distribution of the resident population and jobs as shown in Figure 2 and Figure 3. The positions of jobs show obvious aggregation trends, concentrated in the city center and county center. Compared with the spatial layout of jobs, the distribution of the resident population is more decentralized.

B. JOBS-HOUSING ATTRIBUTE ARPUND URBAN RAIL TRANSIT STATIONS

An index has been proposed to quantify the attribute of the land use around each station. It can be calculated by the number of resident population and jobs within 800 meters from each station as (1).

$$R_i = \frac{N_p^i}{N_p^i + N_j^i} \tag{1}$$

where R_i is the job-resident ratio of land use around station i, N_p^i is the number of resident population within 800 meters from station i. N_j^i is the number of jobs within the 800 meters from station i. R_i equals to 0.5 means the number of resident population equals to the number of jobs around station i. It indicates the land use surrounding station i has the same working and living attribute, which is regarded as the jobs-housing balance. Thus, if the job-resident ratio of land use around station i changes on the interval [0.4, 0.6], we can regard the area around station i is under jobs-housing balance. Otherwise, R_i <0.4, we can regard station i as a working-oriented station, and R_i >0.6 indicates station i is a living-oriented station. Namely, all the stations can be categorized into three different categories.

As shown in the above figure, most stations in Qingdao belong to the living-oriented station. Meanwhile, the phenomenon of agglomeration can be found. Stations belonging to the same category gather together. Almost all stations in Shinan district are under jobs-housing balance. Most stations around May Fourth Square, Jinjialing and Licun commercial area belong to the working-oriented station, such as Licun station (Figure 5). Generally, stations along Shandong road-Heilongjiang road belong to the living-oriented station, such

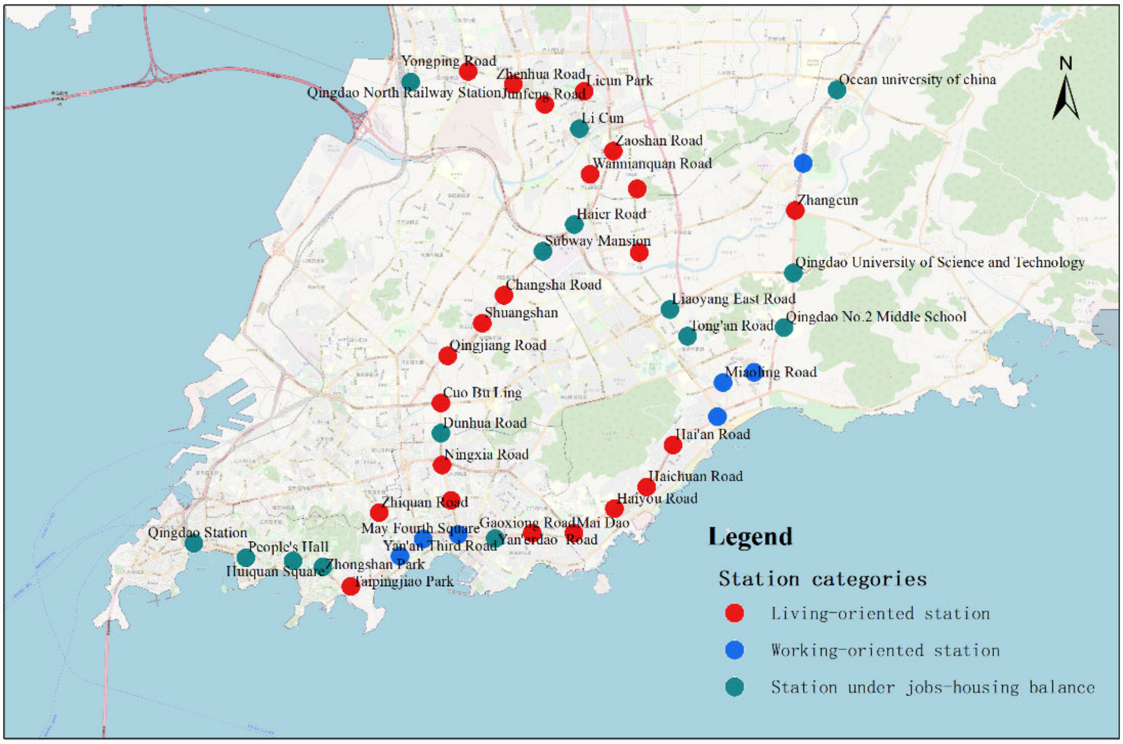

FIGURE 4. Spatial distribution of stations belonging to different categories.

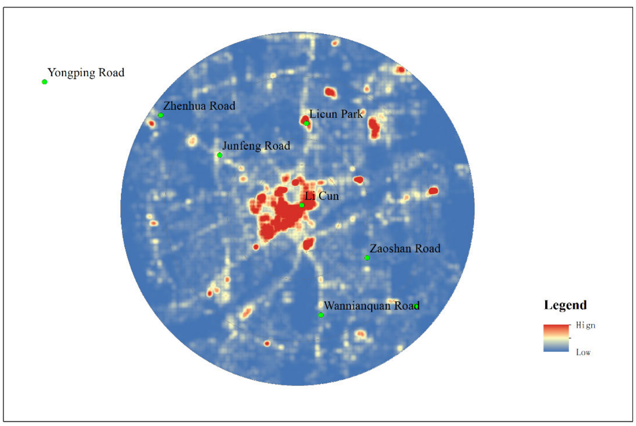

FIGURE 5. Distribution of jobs around Licun station.

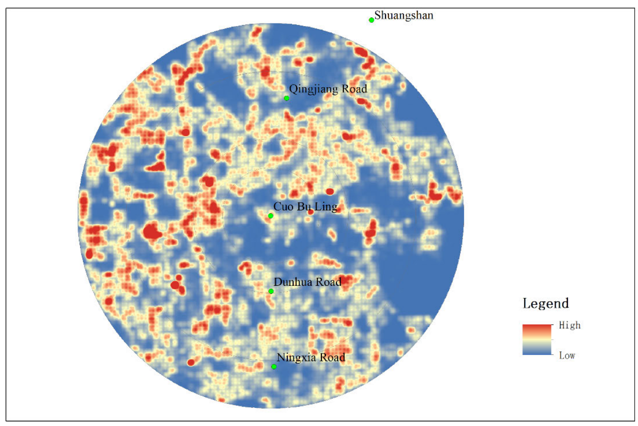

FIGURE 6. Distribution of resident population around Cuobuling station.

as Cuobuling station. As shown in Figure 6, the resident population around this station is very scattered.

C. STATION PASSENGER FLOW

The passenger flow of stations belonging to different categories shows different time-varying characteristics. According to the statistics of entrance passenger flow at each station, the number of entrance passenger flow reaches a peak at the living-oriented stations during 7 am-9 am. Meanwhile, the number of entrance passenger flow has a slight increase during the evening rush hour due to the lack of jobs around the living-oriented stations, such as Cuobuling station (Figure 7). On the contrary, the entrance passenger flow of working-oriented stations has an obvious evening peak, such as May fourth square station in Figure 8. Besides, the entrance passenger flow of stations under the jobs-housing balance is relatively flat, such as Qingdao station.

III. ANALYSIS OF COMMUTING CHARACTERISTICS

A. COMMUTING PASSENGER FLOW

To reduce the influence of tourist passenger flow in tourism-peak season, and to eliminate the effect of the unstable passenger flow due to the opening of metro

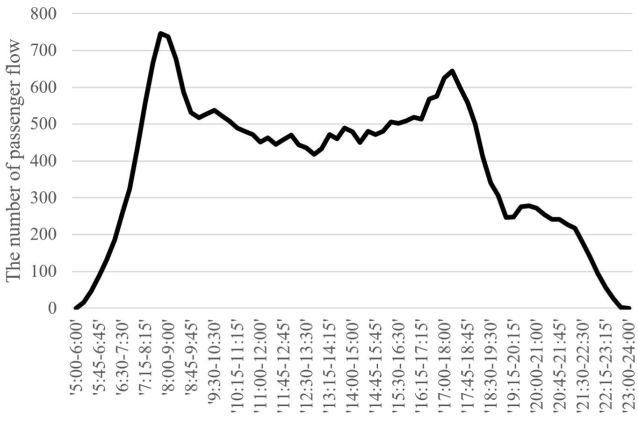

FIGURE 7. Time-varying curve of the entrance passenger flow in Cuobuling station.

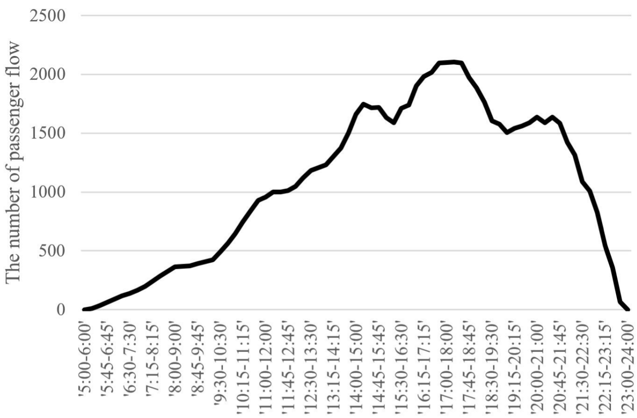

FIGURE 8. Time-varying curve of the entrance passenger flow in May fourth square station.

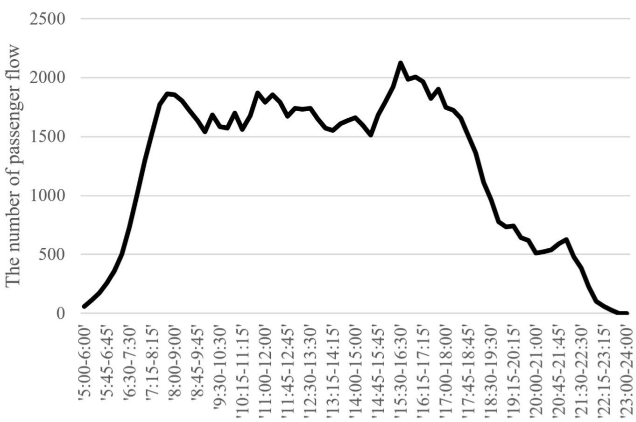

FIGURE 9. Time-varying curve of the entrance passenger flow in Qingdao station.

line 13 (December 2018), we choose the smart card data during November 2018 to analyze the commuting characteristics. The detailed technical roadmap is shown in Figure 10.

We count the number of times the records that the same card number and the same origin-destination (OD) during morning peak hours (7:00-9:00) of a natural month occurred to identify the commuting passenger. The records of the employee ticket and the temporary card are removed. The corresponding result is displayed as shown in Figure 11. The horizontal coordinate is the number of times (days) the records that the same card number and the same OD occurred. The vertical coordinate is the cumulative number of different card numbers. It can be seen that the highest proportion (about 70%) of records is the non-commuting passenger flow. These passengers travel from an origin to a destination only one time in one month. The number of travelers that travel from the same origin to the same destination in all weekdays during one month is 12,656. Considering the influence of uncertain factors such as vacation and business trips, it is assumed that the commuters will travel more than 15 times from the same origin to the same destination during one natural month is 15. Namely, the threshold to identify one traveler is commuter is 15 days. Thus, there are 42,600 commuter passengers, accounting for 10% of all passengers. The proportion of commuters in all passengers under different value of threshold is given in Table 1.

TABLE 1. The proportion of commuters in all passengers under different value of threshold.

Threshold (days)	Cumulative number of commuters	Proportion of commuters in all passengers
10	66315	15.79%
11	60724	14.46%
12	55900	13.31%
13	51343	12.22%
14	46855	11.16%
15	42577	10.14%
16	38290	9.12%
17	34171	8.14%
18	30091	7.16%
19	25895	6.17%
20	21557	5.13%
21	17191	4.09%
22	12656	3.01%
23	8017	1.91%
24	3709	0.88%
25	2397	0.57%
26	1466	0.35%
27	726	0.17%
28	226	0.05%
29	109	0.03%
30	39	0.01%

B. ANALYSIS OF PASSENGER FLOW IN DIFFERENT STATIONS

Under the assumption that the threshold is 15, we analyze the commuting passenger flow in different stations in this subsection. Because commuters almost arrive at the original station at the same time every weekday. It can be used to analyze the spatial cluster of passenger flow. Here, the proportion of commuters to the passenger flow during the morning peak is used to describe the clustering degree of spatial distribution. From the perspective of temporal distribution and spatial distribution, all the stations can be classified into 5 categories as follows:

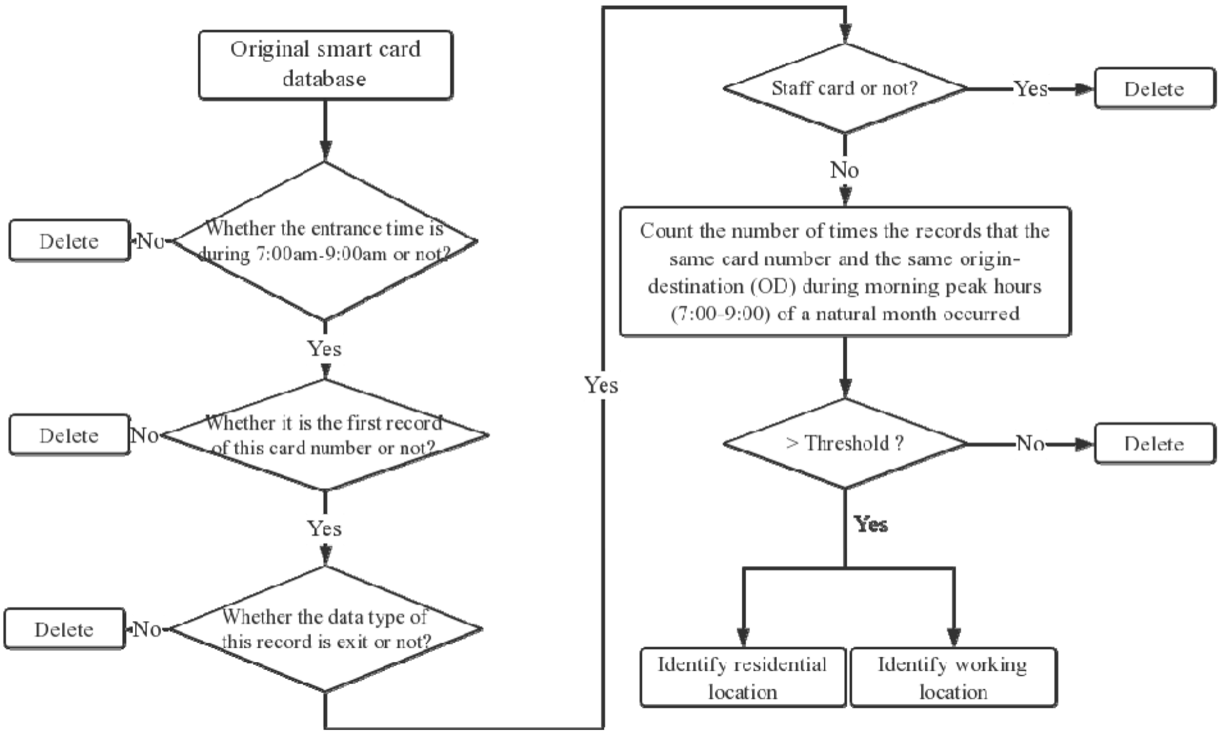

FIGURE 10. Technology roadmap for commuting passenger identification.

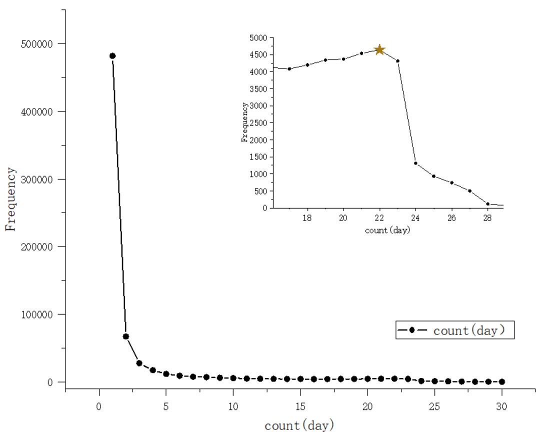

FIGURE 11. The cumulative number of travel times for passengers during 7:00am-9:00am of one month.

(1) The temporal distribution of passenger flow is uneven. The spatial distribution of commuting passenger flow is agglomerate.

The typical feature of these stations is that the proportion of passenger flow during the morning peak to the passenger flow of the whole day is more than 50%. Besides, the proportion of commuters to passenger flow during the morning peak is also more than 50%. As shown in Figure 12, the temporal distribution of passenger flow in Zhenhua road station, Changsha road station, Licun park station, Junfeng road station, and Hualoushan road station is uneven. It is worth noticing that the spatial position of these stations can be seen in Figure 4. The main task of these stations is to serve the commuting passengers during the morning peak.

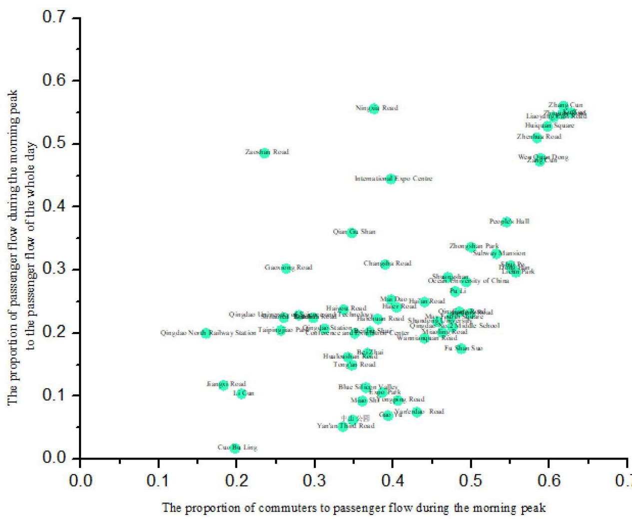

FIGURE 12. The relationship among commuting passenger flow, passenger flow during morning peak hours and passenger flow of the whole day.

(2) The temporal distribution of passenger flow is even. The spatial distribution of commuting passenger flow is non-agglomerate.

The typical feature of these stations is that the proportion of passenger flow during the morning peak to the passenger flow of the whole day is less than 20%. Besides, the proportion of commuters to passenger flow during the morning peak is also less than 20%. As shown in Figure 12, the temporal distribution of passenger flow in International expo centre station, Conference and exhibition center station, Qiangushan

TABLE 2. Correlation analysis between resident population and commuting passenger flow.

	Entrance passenger flow	Exit passenger flow	Number of the surrounding population	Number of the surrounding jobs
Entrance passenger flow	1.00	-	-	-
Exit passenger flow	0.09	1.00	-	-
Number of the surrounding population	0.78	0.36	1.00	-
Number of the surrounding jobs	0.41	0.84	0.67	1.00

station and Blue silicon valley station is even. The main task of these stations is to serve the non-commuting passengers.

(3) The temporal distribution of passenger flow is even. The spatial distribution of commuting passenger flow is relatively agglomerate.

The typical feature of these stations is that the proportion of passenger flow during the morning peak to the passenger flow of the whole day is less than 20%. However, the proportion of commuters to passenger flow during the morning peak is between 20% and 50%. As shown in Figure 12, the temporal distribution of passenger flow in May fourth square station, Fushansuo station, Yan'an third road station, Miaoling road station, and Taipingjiao park station is even. Meanwhile, a considerable percentage of passengers during the morning peak is commuting passengers.

(4) The temporal distribution of passenger flow is relatively uneven. The spatial distribution of commuting passenger flow is relatively agglomerate.

The typical feature of these stations is that the proportion of passenger flow during the morning peak to the passenger flow of the whole day is between 20% and 50%. Besides, the proportion of commuters to passenger flow during the morning peak is also between 20% and 50%. As shown in Figure 12, the temporal distribution of passenger flow in Zhangcun station, Ocean university of china station, Shandong university station, Qingdao No.2 middle school station, and Qingdao station is relatively concentrated. Similarly, a considerable percentage of passengers during the morning peak is commuting passengers.

(5) The temporal distribution of passenger flow is relatively uneven. The spatial distribution of commuting passenger flow is agglomerate.

The typical feature of these stations is that the proportion of passenger flow during the morning peak to the passenger flow of the whole day is between 20% and 50%. However, the proportion of commuters to passenger flow during the morning peak is more than 50%. As shown in Figure 12, the temporal distribution of passenger flow in Qingjiang road station, Cuobuling station, Licun station, Subway mansion station is relatively concentrated. Furthermore, more than 50% of the passenger flow during morning peak is commuting passengers.

C. ANALYSIS OF ORIGIN-DESTINATION COMMUTING DEMAND

As shown in Figure 13, most commuting passengers travel from north to south and from east to west. Among all the OD travel demand from north to south, the travel demand between Licun station and Dunhua road station, Licun park station, and Miaoling road station are the greatest, which reach up to 650. Meanwhile, among all the OD travel demand from east to west, the travel demand between Qingdao station and May fourth square station is the greatest, which reach up to 420.

FIGURE 13. The main directions of commuting passenger flow (commuting passenger flow> 100).

As described in Section 2.2, two different categories of stations Licun station (living-oriented station) and Qingdao station (station under jobs-housing balance) are selected as the analysis object in this subsection. Based on the statistics of identified commuting passenger flow, it is found that 10% of commuting passengers' original station is Licun station. Besides, as shown in the left-hand side (LHS) of Figure 14, the most destination of commuters from Licun station is in the south area of the city, such as Dunhua road station in Shibei district, May fourth square station in Shinan district, Miaoling road station in Laoshan district.

Similarly, it is also found that the number of commuting passengers originating from Qingdao station reaches more than 2,325. It is about 5% of the total number of commuting passengers. Most commuting passengers of Qingdao station travel from east to west as shown in the right-hand side (RHS) of Figure 14. Besides, the detailed destinations of commuting passengers from Licun station and Qingdao station can be seen in Figure 15.

FIGURE 14. The spatial distribution of commuting passenger flow (LHS: Licun station, RHS: Qingdao station).

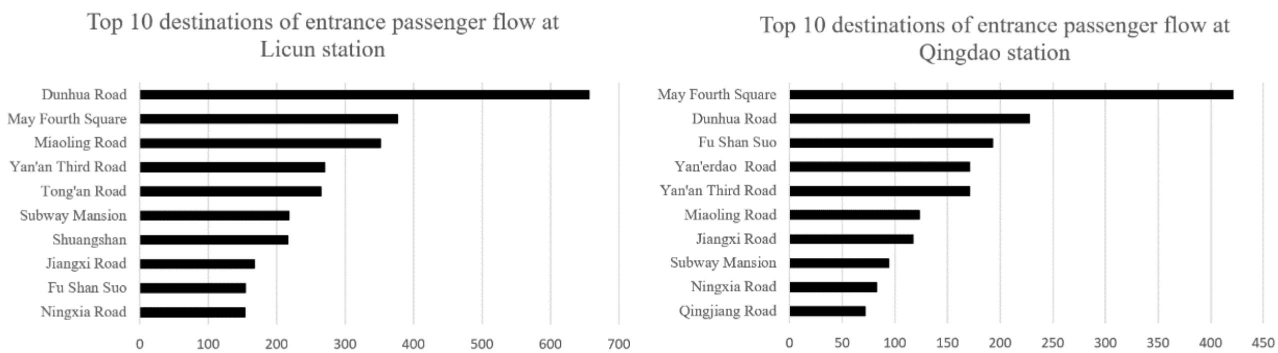

FIGURE 15. Top 10 destinations of entrance passenger flow.

IV. CORRELATION ANALYSIS BETWEEN RESIDENT POPULATION AROUND THE STATION AND COMMUTING PASSENGER FLOW

Generally, it is believed that there is a certain correlation between the resident population around the station and the passenger flow. Based on the statistical analysis software, more detail results can be further discovered as shown in Table 2. There is a strong correlation between the number of entrance passenger flow and the number of resident population around the station. Correlation coefficient up to 0.78. Meanwhile, there is a strong correlation between the number of exit passenger flow and the number of jobs around the station. The corresponding correlation coefficient is 0.84.

V. CONCLUSION

This paper aims to extend the related studies on transportation and land use based on the massive internet data of urban planning and traditional data resources of the traffic system. Through the combination and mining of internet-based positioning data and smart card data, we use the case study of Qingdao city in China to identify the jobs-housing relationship around urban rail transit stations. All the stations are classified into three different categories: living-oriented station, working-oriented station, station under jobs-housing balance. Besides, as for the connections of different regions and the spatial distribution of the urban population, the method of smart card data mining is adopted to analyze commuting characteristics and spatial distribution of origin-destination travel demand for different categories of stations. Finally, analysis of the correlation between the resident population around urban rail transit stations and commuting passenger flow is carried out by statistical methods.

Based on the works accomplished above, our analysis yields some interesting insights. First, we found that compared with the spatial layout of jobs, the distribution of the resident population is more decentralized. Second, most stations in Qingdao belong to the living-oriented station. Meanwhile, the phenomenon of agglomeration can be found. In general, all stations belonging to the same category gather together. Third, due to the spatial distribution of jobs and residential locations, most commuting passengers travel from north to south and from east to west.

This study focuses on transportation and land use problems based on the massive data of urban planning and traditional traffic data. In the near future, with the coming of the big data age, more data resources and methods of data mining can be used to identify the jobs-housing relationship and commuting characteristics in detail.

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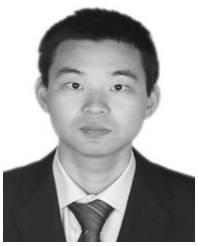
TONGFEI LI received the Ph.D. degree in system science from Beijing Jiaotong University, in 2018, and the joint Ph.D. degree from the National University of Singapore, supported by the China Scholarship Council, in 2017. Since 2018, he has been a Lecturer with the College of Metropolitan Transportation, Beijing University of Technology, Beijing, China. His research interests include transportation and land use, ridesharing, and connected automated vehicle.

YANYAN CHEN received the Ph.D. degree from the School of Civil Engineering, Harbin Institute of Technology, Harbin, China, in 1997. From 2004 to 2005, she was a Visiting Scholar with the Center for Transport Studies, Imperial College London, London, U.K. She is currently a Professor with the College of Metropolitan Transportation, Beijing University of Technology, Beijing, China. Her current research interests include traffic big data, transportation planning and management, intelligent transportation, system simulation, and network optimization.

ZHEN WANG received the B.S. degree in transportation from the Shandong University of Science and Technology, Qingdao, China, and the M.S. degree in transportation planning and management from Beijing Jiaotong University, Beijing, China. He is currently an Engineer with the Qingdao City Planning and Design Institute. His research interests include big data analysis, travel behaviors analysis, and urban spatial analysis.



ZHUO LIU received the B.S. degree in environmental science from the School of Environment, Beijing Normal University, China, in 2012, and the master's and Ph.D. degrees in environmental design from the Urban Planning Laboratory, Kanazawa University, Japan, in 2014 and 2017, respectively, supported by the Scholarship of Japanese Government. He is currently a Lecturer of urban transportation planning with the College of Metropolitan Transportation, Beijing University of Technology. He has been active in recent years in uncovering the connection between urban land use and transportation. His research interests include integrated planning of land use and transportation, planning support systems, agent-based simulation for urban policies, and evaluation of urban transportation systems.

RUI DING (M'85) received the B.S. degree in land resources management from Sichuan Agricultural University, China, in 2007, the M.S. degree in agricultural extension, land resources management from the School of Resources and Environment, Sichuan Agricultural University, in 2012, and the Ph.D. degree in urban planning and design from University Putra Malaysia, Malaysia, in 2018.

From 2007 to 2014, he was an Assistant Engineer with the land-use planning and farmland protection affairs of Anyue County Bureau of Land and Resources, and Farmland Land Protection Department, Land and Resources Department of Sichuan Province. Since 2018, he has been an Assistant Professor with the College of Big Data Application and Economics, Guizhou University of Finance and Economics. His research interests include the urban planning, land resources management, traffic planning, complex traffic networks analysis, and GIS.

SHUQI XUE received the Ph.D. degree in system science from Beijing Jiaotong University, in 2018. Since 2018, he has been a Lecturer with the School of Modern Posts, Xi'an University of Posts and Telecommunications, Xi'an, China. His research interests include bicycle traffic, pedestrian flow, and pedestrian evacuation.