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Research Article

A Study on the Calculation of Platform Sizes of Urban Rail Hub Stations Based on Passenger Behavior Characteristics

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The Chinese national rail transit design specification decides the size of urban rail transit platforms in China. This suggested method treats passengers as homogeneous individuals when calculating the walking area within a platform. However, the heterogeneity of passenger behavior in a rail hub station has not been considered. It is not reasonable to see passengers as homogeneous individuals. In this study, by observing passenger behavior characteristics at rail hub platforms, two parameters were obtained, walking speed and luggage size. Passengers were then accordingly put into different groups, and dynamic spatial demands for each passenger group were calculated by parameter fitting functions. Based on the theory of spatiotemporal consumption, the nonlinear constraint model was constructed to determine the space-time consumption of each passenger group, and finally the area demands of different types of passengers were obtained for different time and passenger flows. An application was made to Beikezhan Station on Xi'an Metro line 2. The calculation results show the area demands ranges of four passenger groups with distinct characteristics, and their space-time consumption varied. The study can calculate the space demands for all passenger varieties within a rail hub transit platform and provide suggestions for the determination of the ideal walking area size of rail transit platforms.

1. Introduction

Similar to other infrastructure projects, rail transit requires large investment and a long construction period. Planning and design should therefore be undertaken with caution. The construction of urban rail transit lines includes two aspects, namely, rail transit stations and interstation tunnel sections. The cost of building one meter of a station is approximately 2.4 times greater than that of an interstation tunnel section [1]. An oversized platform will increase the costs and may not provide a return on investment. On the other hand, if the platform is too small, it will not be able to cater to a large passenger flow. For example, at Beijing metro line 13, Xierqi Station's original design was too small to meet the transfer needs of the Changping line [2]. The council had to abandon the old station due to high risks in reconstructing the existing one. In China, the current metro design codes provide formulae to calculate platform widths. The formulae are shown in equations (1)–(4) [3], and the specific references of the parameters in the formulae are shown in Figure 1.

$$B_c = b + z + t, \tag{1}$$

$$B_d = 2b + n \cdot z + t, \tag{2}$$

$$b = \frac{Q_{\text{up}} \cdot \rho}{L} + b_a, \tag{3}$$

$$b = \frac{Q_{\text{up\&down}} \cdot \rho}{L} + M, \tag{4}$$

where B_c is the side platform width in meters, B_d is the island platform width in meters, b is the side platform width in

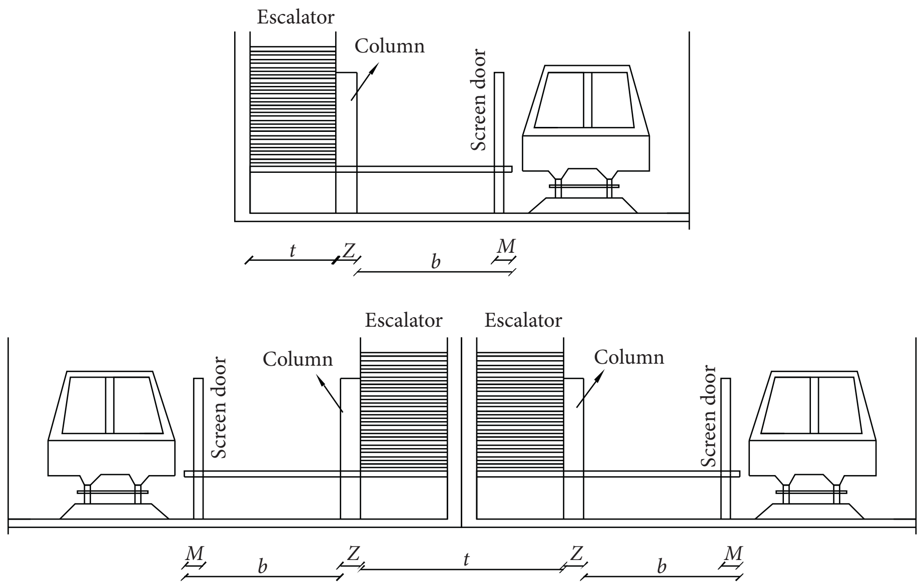

Figure 1: Diagram of a side platform and island platform.

meters, n is the lateral column number in meters, z is the longitudinal beam width in meters, t is the sum of the passenger staircase and escalator widths, denoted in meters, Q_{up} is the forward or passenger flow control period, which is the designed passenger flow per train at the ultrahigh peak hour on one side, $Q_{up\&down}$ represent the long-term or passenger flow control period, which is the designed passenger flow on and off through one side per train at the ultrahigh peak hour, ρ is the flow density on the platform, measured in passengers/m^2, L is the calculated length of a platform in meters, M is the distance from the edge of a platform to the inside of the platform gate column, where $M = 0$ without a platform gate. Finally, b_a is the safety protection width of the platform, typically 0.4 m, and M is used instead of b_a when a platform gate is used. There is an assumption in the current guidelines at home and abroad that all passengers are homogeneous when calculating the width of a platform. The distinction among passenger behavior has been ignored.

In China, the side platform width is calculated by using passenger flows boarding and getting off on one-way trains, and the island platform width is achieved symmetrically. In Japan, the total number of passengers on the uplink and downlink is used to determine the platform width, that is, $Q = Q_{up} + Q_{down}$, as seen in equations (3) and (4). In Europe and America, the size is typically empirically calculated [4]. The value of the recommended parameters is undecided and has considerable randomness. To achieve a balance between the construction costs and passenger demands, scholars are committed to making corrections to existing methods. Shen divided the distribution of passengers on the platform into three states, namely, the even distribution when waiting to board, the assembling state before boarding, and the distribution when getting off the train [5]. The size of the platform was converted into the sum of the corresponding areas of the three states. Meanwhile, the area value was revised in the context of the peak passenger flows and the transfer of sudden passenger flows. Liu and Zhu [6] divided the platform area into a static area and a dynamic area according to the performance states of passenger flows. The sum of the dynamic and static areas is the platform size. Although these studies divided the station area, this is a revision of the standard method. The differences between stations and the characteristics of passengers have not been considered.

Tang and Yang [7] studied the passenger characteristics of an urban rail transit platform. Based on the video data gained from the platform of Xizhimen Station, Beijing Metro Line 2, the system analyzed passenger behavior, walking speed, distribution, and density whilst waiting to board. However, no connection between passenger characteristics and the size of the station platform was established. The practical significance is not strong when only passenger behaviors are studied. The strides and speeds of passengers are important parameters of the individual characteristics and play an important role in determining the sizes of facilities. Kirsch proposed that passengers tend to walk at a certain distance from others and obstacles. That is, passengers have certain space demands when walking [8]. Yan and Chen divided the space demands into static and dynamic ones, where static space demands are smaller than dynamic space demands [9]. There are two kinds of static states in subway stations, namely, the queue state, including ticket purchasing, ticket checking, queueing for escalators, and getting on and off trains, and the waiting to board on the platform state [10]. When not queuing and waiting to board, passengers will probably continue to walk along the platform. They typically do not stay close to one another but instead keep a certain distance, that is, there is a dynamic space need for passengers [11]. The composition of passengers on the platform, their pace, and the size and density of luggage carried are all factors affecting space needs. Thus, the type of passenger flow determines the platform size [12]. Therefore, it is a good idea to study the relationship between passengers' space needs and platform size through passenger characteristics and thus develop a method to solve the ideal size calculation of a platform. In reality, different passenger flows show different demands for space [13]. For example, the proportion of passengers carrying luggage at commuter stations is relatively low, while in large-scale transportation hubs, passenger structures are more complicated, where the proportion of passengers carrying luggage is higher and a larger amount of space is required by individuals. Therefore, with the same passenger flow, the suitable sizes for these two types of stations are different. Taking Xili Station in Shenzhen as an example, it was designed to cater for 3 lines without considering its potential for becoming a comprehensive transport hub [14, 15]. Its space needs will increase with more people carrying luggage; thus, the size suggested when following the national guidelines is not enough during peak hours. The calculation method given in the existing standard guidelines appears to have been too simple and based mainly on experience. It fails to provide advice on the construction of a large transport hub with distinct passenger flows [16, 17].

From the above, studies on the width calculation method of the urban rail transit platforms have not been sufficiently developed, and related experimental studies on passengers' walking behaviors on platforms are not sufficiently thorough enough to guide modeling research. Models that can reflect real passenger platform behaviors and those that enable the calibration of the key parameters are lacking. As a consequence, it is not possible to assess the actual demand for the platform area without quantitative passenger behavioral characteristics analysis. Therefore, a more realistic model is needed. For filling these gaps, this paper aims to discover the internal functional relationship of passenger group behavior parameters by using field survey data and establish an individual passenger walking area demand model to calculate the platform area from the individual perspective. Moreover, the intrinsic relationship and demand model of passenger behavior parameters explored in this paper provides a general method for analyzing the platform size of a rail transit hub station.

In this paper, the relevant work arrangements are as follows: Section 2 introduces the model, describing in detail the functional relationships and derivations that exist between the passenger behavior parameters and constructing a spatiotemporal demand model to determine an ideal platform area. Section 3 is mainly the collection and processing of the experimental data, combined with the survey scheme, and the calibration model parameters of the object data. Section 4 illustrates the implementation of the passenger area demand model through programming and application analysis. The conclusions and future recommendations are discussed in the final section.

2. Model Specification

2.1. Passenger Characteristics and Spatial Demand Analysis. Urban rail transit hubs are relatively closed traffic spaces. People in enclosed spaces tend to have poor orientation and a faster speed than usual. The average walking speed of Chinese passengers in a closed transportation hub for the purpose of transfer is 1.49 m/s, which is faster than that of the people who shop in a shopping mall (1.16 m/s) and pedestrians walking in leisure areas (1.10 m/s). William proposed that the average walking speed of Hong Kong urban rail transit passengers was 1.37 m/s. The crowd density on urban rail transit platforms and the walking speed of passengers were investigated and compared with data published in other research materials [18–20]. Then, the relationship between crowd density and walking speed was analyzed using a regression model based on the survey data. The nonlinear functional relationship shown in equation (5) was then obtained:

$$y = 0.39x^2 - 1.57x + 1.84, \tag{5}$$

where x is passenger flow density on the platform. In equation (5), at 95% confidence interval, the walking speed range is 0.393–1.40 m/s in the model, and it follows a normal distribution.

Unlike ordinary stations, passengers carrying luggage in hub stations are often seen in large numbers, which is an important factor affecting the density of standing passengers per capita. Carrying luggage will increase the average moving area of a passenger. When the proportion is large, the platform area originally designed as 0.5 m^2/person is now too small for passenger movement. The difference between ordinary stations and large transport hub stations is the proportion of passengers carrying luggage. They account for only 2% of passengers in ordinary stations, whereas in large hubs, especially rail transit stations connecting with external transport hubs, nearly 30% of passengers carry bags or suitcases. The figure of stations connecting to external transportation hubs is about 0.05 m^2/person larger than that of an ordinary station [21]. If the number of passengers waiting for a train is 300, the platform size required by a hub station is 15 m^2 larger than that of an ordinary station. To further analyze the space demands of passengers carrying luggage, they were classified into the following two categories, namely, class A—passengers carrying bags or small pieces of luggage, and class B—passengers carrying trailers or large pieces of luggage. The area occupied by the luggage according to its vertical projection is in following order: Class A—0.25 m^2 and class B—0.5 m^2 [22].

Passenger space demands include both static and dynamic space demands, among which the static space demands are less than the dynamic space demands, where both decrease with an increase in passenger density. It can be seen that the passenger distribution scale of platforms is large, where the passenger features are diverse and have a complex composition. The previous simple method of calculating the space occupied by individuals cannot meet the demands, so it is necessary to conduct quantitative analysis of passengers according to their characteristics. Crowd density is one of the main reasons for a restriction in the pace of passengers. Here, passengers are divided into different groups according to the size of the space occupied by their luggage [23]. In this way, there is a certain spatial distance between two adjacent passengers when they move in a group, and this distance should be regarded as dynamic. It changes in different passenger groups. A passenger group carrying class A luggage, which needs more space, thus makes the space between passengers larger. On the contrary, the space between the passengers carrying class B luggage is smaller. This space varies in different groups, within which the density varies. By fitting the data values extracted from the different groups, a relationship between the interpassenger space and the density of a group has been gained, shown as in Figure 2. It can be seen that when the space is big, the density of passenger groups is kept at a low level. Density here refers to the number of passengers per unit area, where the area includes the size of the ground occupied by the luggage.

The pace of the passenger group is another important factor related to the distance between two adjacent passengers. The speed of passengers carrying luggage with wheels is higher than that of the passengers with luggage without wheels. To quantify this relationship, the observed sample data were fitted, and the obtained results are shown in Figure 3. The results show that there is an intrinsic correlation between interpassenger space and group speed. This correlation is nonlinear, as the space between passengers is a variable parameter which is unstable and affected by the speed of surrounding passengers. The method for calculating the passenger dynamic space demands, determined through studying Figures 2 and 3, will be given in the following sections.

The dynamic distance between passengers is largely affected by the passenger group density and speed, different sight distances, and whether passengers travel with companions. These factors are difficult to verify in the survey and are therefore considered as an error term. According to the fitting function and analysis of Figures 2 and 3, the second-order polynomial distribution of the passenger dynamic space obeying the density and the speed was determined, and thereby the model was established:

$$d = a_1 v^2 + a_2 v + a_3 \rho^2 + a_4 \rho + a_5. \quad (6)$$

For the boundary constraint, the limited space distance was analyzed from the observation when the walking speed was 0. Under low-density conditions, the average space distance between two adjacent passengers is about 1.85 m and the average crowd density is 0.43 p/m^2. When crowded, the average interpassenger spacing is about 0.72 m, and the average crowd density is 2.14 p/m^2. Therefore, the boundary conditions in these two scenarios were brought into equation (6) so that the model satisfies the following two constraints:

$$1.85 = a_3 \times 0.43^2 + a_4 \times 0.43 + a_5, \quad (7)$$

$$0.72 = a_3 \times 2.14^2 + a_4 \times 2.14 + a_5, \quad (8)$$

where a_1 to a_5 are undetermined coefficients and equations (7) and (8) represent the shortest spacing of static passengers in noncrowded and crowded situations, respectively. The calibration results are shown in Table 1. Finally, the calculation method of the distance between passengers is gained, shown in equation (9). The relative error distribution shows that 55% of the errors are within 10% and that the absolute error, ε, obeys a normal distribution (0.0013, 0.21032).

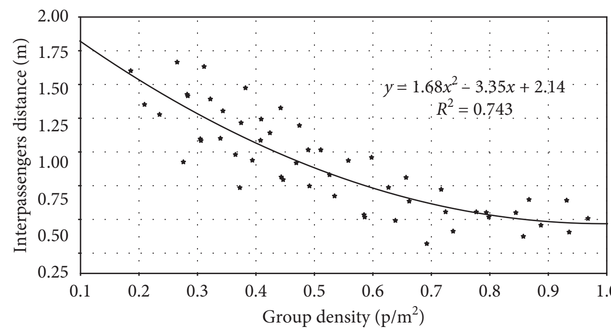

FIGURE 2: Scatter diagram of group density and the distance between passengers.

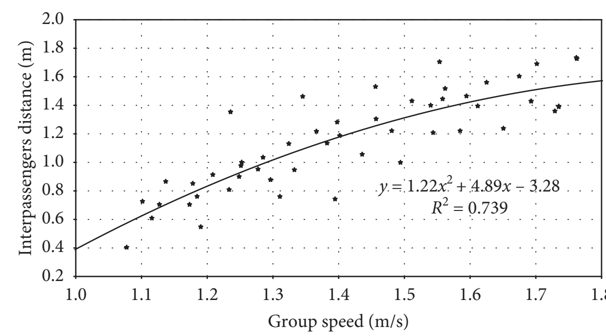

FIGURE 3: Scatter diagram of group speed and the distance between passengers.

$$d = 6.074v^2 - 11.226v - 1.210\rho^2 + 0.070\rho + 4.35 + \varepsilon. \quad (9)$$

Generally, the space occupied by an individual is regarded as an ellipse [24], especially when they walk slowly in a high-density crowd. The space demand of a passenger can be described using the projection of their body with their belongings. Taking the shortest distance as a radius, the dynamic space demand of a passenger can be determined according to the following equation:

$$S = \frac{\pi}{4} \times d \times \frac{\alpha}{\beta} \times d = \frac{\alpha\pi}{4\beta} d^2, \quad (10)$$

where d represents the distance between adjacent passengers, which can be obtained by equation (9), and α and β represent the front width and side width that a passenger occupies. α and β values of individuals carrying different forms of luggage are shown in Table 2.

2.2. Platform Size Optimization Model Based on Spatiotemporal Consumption. With the arrival of a train at a certain time, the flow of people in the station appears to rise sharply. This lasts for a period of time, and then the flow of people gradually decreases. This cycle is repeated [25]. It is similar to the pedestrian behavior at intersections where signals are in operation. The platform needs to fulfill the spatiotemporal demands of passengers arriving at the platform at such intervals, such as to act both timely and efficiently.

Table 1: Calibration results of the model parameters.

Parameter	Estimate	Standard deviation	95% confidence interval Lower bound	Upper bound
a_1	6.074	2.102	3.663	8.473
a_2	−11.226	0.157	−15.310	−7.135
a_3	−1.210	2.331	−6.331	3.911
a_4	0.070			
a_5	4.350			

Table 2: α and β values of passengers with different forms of luggage.

Luggage	α (m)	β (m)	Area (m^2)
No luggage or carrying small pieces	0.51	0.35	0.18
One bag or more than one small piece	0.65	0.45	0.29
At least one trailer or more bags	0.85	0.65	0.55

2.2.1. Model Construction and Behavior Analysis of a Passenger Group. A passenger group is not a simple superposition of individual passengers, where its composition is affected by passenger behaviors and the surrounding environment. A passenger group is also not a static concept. With the passage of time and different stimuli, passengers present dynamic changes in their size and composition. The dynamic change and disappearance of passenger groups is defined as the dynamic nature of a passenger group. The passenger group in this model is the set of passengers with the same characteristics. To this end, the formula $E\{g[p_1, p_2, \cdots p_m], G[G_1, G_2, \cdots G_n], F[F_1, F_2, \cdots F_c]\}$ is used to represent the platform environment of passengers, and g, G, and F are used to represent the passenger set, passenger cluster, and full-day train arrival time set, respectively. Here, G_i represents the i^{th} passenger group, p_1, p_2, and so forth represent passenger individuals, and g_{ij} represents passengers in different passenger groups, where j is a passenger group. When $j = 1$, 2, or 3, g_{11} is passenger 1 in group 1, g_{21} is passenger 2 in group 1, g_{31} is passenger 3 in group 1, and so on, and the total number of members of the group at time t called the size of the group, shown as follows: $S(G_i) = \sum_i j\{j \mid g_{ij} \in G_i\}$. Thus, the modeling of passenger groups becomes a problem of studying the internal relationship between individual behavior (g_{ij} and G_i) over time and the spatial state, while the behavior problems of passenger groups represent the study of the external relationship between g, G, and F.

2.2.2. Spatiotemporal Consumption Model of Passenger Clusters. Spatial-temporal consumption refers to the space occupied by an individual (person or vehicle) at a certain time or the time spent in a certain space. The process of passengers entering, getting on, or leaving the platform produces the spatiotemporal consumption of the platform. At the same time, the space-time consumption value of a passenger cluster G_i appears in the platform area. The space-time consumption value of each passenger group is determined by using the space-time consumption calculation formula:

$$\overline{C_i} = \frac{\sigma \sum_j^{N_i} C_j}{N_i} = \frac{\sigma \sum_j^{N_i} S_j T_j}{N_i}, \tag{11}$$

where $\overline{C_i}$ is any time when a train arrives at the station, which represents the group average space-time consumption value of passenger group G_i on the platform, measured as $m^2 \cdot s$, N_i is the cumulative total of passenger group G_i on the platform at any time when a train arrives at the station; C_j is the time and space consumption of passenger group G_i appearing at the j^{th} time, S_j is the platform space required by passenger group G_i appearing at the j^{th} time, measured in m^2, which can be calculated by equation (10). Additionally, T_j is the time taken by the j^{th} passenger group G_i from arrival to departure the platform in seconds, L_j is the distance taken by the j^{th} passenger group G_i from arrival to departure the platform in meters, v_j is the speed taken by the j^{th} passenger group G_i from arrival to departure the platform in m/s, and σ is the fluctuation factor in the passenger group. In special cases, such as bad weather or traffic control, the station will only allow passengers to exit and not allow them to enter the station, thereby reducing the passengers on the platform significantly. At this time, the volume of different passenger groups will fluctuate greatly. Therefore, a fluctuation factor σ is introduced to characterize the change of passengers in special circumstances. In this study, the space-time consumption method is used to determine the platform size without considering these special conditions, so the factor σ is equal to 1.

Different passenger groups divided by their travel characteristics have different space-time consumptions. Meanwhile, at any moment F_i from the arrival time set $F[F_1, F_2, \cdots F_c]$, the dynamic environments passengers belong to are different, shown differently for the number of passenger evacuation platforms, passenger group frequency, and the number of the group members of each type of passenger group. No matter how these factors change, the platform needs to meet the temporal and spatial demands for the timely and safe movement of all passenger clusters of $G[G_1, G_2, \cdots G_n]$. For E_i, the environment of each platform, the space-time consumption of passenger clusters can be obtained. Then, according to the daily train running plan, an objective function may be established to calculate the space-time demand that the platform should fulfill each time a train arrives at the station.

The constraint condition of the model for any state in the platform environment E_i was analyzed. For state E_i, further clarification of the three-layer set is required to determine the parameters and constraints of the model. On the first layer, the arrival time of a day set of $F[F_1, F_2, \cdots, F_c]$ is determined according to the train operation plan. The set obviously includes the peak and off-peak times, assuming that the time F_i is taken. On the second layer, the passenger cluster $G[G_1, G_2, \cdots, G_n]$, under moment F_i, indicates that all passengers on the platform at this time will be divided into their respective clusters. It is clear that the number of passenger clusters is at least under $n \geq 2$, depending on the specific situation. In the third layer, for any passenger cluster G_i, it contains a set $g[g_1, g_2, \cdots, g_m]$, where $m \geq 3$. For any passenger g_i on the platform, the space required can be calculated by equation (12), which is expressed as follows:

$$S_i = \frac{a\pi}{4b} d_i^2. \quad (12)$$

Passengers undertaking business trips and others who greet and send off relatives and friends increase the number of passengers on the platform. The actual numbers on the train are represented as D in the Equation, and its value was obtained from Xi'an Metro. If passengers are divided into n clusters, and the number of passenger members g_{ij} contained in any cluster G_i is m, then the total number of passengers on the platform area is the sum of the number of members in all passenger clusters. Equation (13) expresses this:

$$\sum_{i=1}^{n} \sum_{j=1}^{m} g_{ij} > D. \quad (13)$$

Any passenger cluster in the platform area occupies a certain amount of platform space in a certain period of time from arrival to departure. In order to meet the aforementioned spatiotemporal demands, the platform can provide a maximum threshold value in space, that is, the scale S of the planned design or the built platform. The time threshold is the interval between two trains, τ, that is, the maximum waiting period at the platform and the passenger moving time. The accumulation of the space-time consumption value of all passenger clusters should be less than the maximum value that can be provided, which can be expressed by

$$\sum_{i=1}^{n} \sum_{j=1}^{m} S_{ij} \times t_{ij} \leq S \times \tau. \quad (14)$$

Finally, through the above analysis and via combination with equation (11), the average space-time consumption value of G_i for each passenger cluster with a_i frequency on the station platform can be obtained, which can be expressed by

$$\overline{C_i} = \frac{\sigma \sum_i \sum_{j=1}^{m} S_{ij} \times t_{ij}}{a_i}. \quad (15)$$

Objective function: Considering the distribution of passenger flows at peak times during a day, the objective function must be the space-time consumption values of platform passenger flows belonging to the set $F[F_1, F_2, \cdots, F_c]$; thus, in order to solve the ideal size calculation of a platform, one should obtain the maximum of the objective function, namely, to make the platform area space-time consumption at a maximum. This is represented in the following equation:

$$\max Z = \frac{\sum_{i=1}^{n} \overline{C}_i \times a_i}{\sum_{i=1}^{n} \overline{t_i}}. \quad (16)$$

The model was implemented to process the data obtained through programming. The procedure is shown in Figure 4.

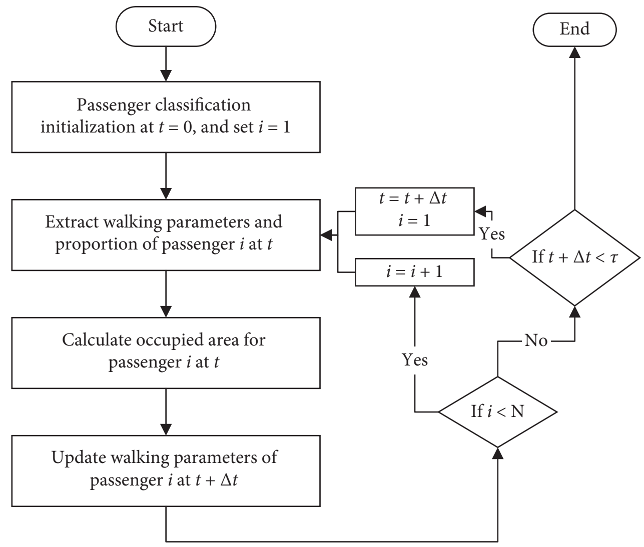

Figure 4: Model implementation framework.

3. Data

3.1. Data Collection. The data were collected from Beikezhan Station on Xi'an Metro line 2. To study the characteristics of passengers on the platform and their behaviors, a practical and feasible method is necessary. High-resolution cameras were used on the platform to collect the data. A Samsung HMX-F90 camera with 5-megapixel resolution, capturing 720p images, was used to record data for 2 hours continuously. The camera was secured to the ceiling, 6 meters from the platform floor, with a view range of 0–90 m. As shown in Figure 5, three cameras were arranged longitudinally along the platform to ensure that the passengers' activity area was fully covered.

For the arrival and leaving behaviors of passengers on platforms, it is necessary to investigate the actual station scenario. For the extraction and analysis of the original data, considering the influence of contingency, the selection of investigation time is not completely continuous. From June 15^{th} to July 15^{th}, 2018, during weekdays, 15 video data collections were conducted during weekdays. The survey time was from 08:00 to 23:00, with each implementation lasting 2 hours. Within the two hours, the first hour covers the last hour in the previous survey, as shown in Figure 6. The solid blue line represents the 1^{st} two hours, 3^{rd} two hours, 5^{th} two hours, etc., and the 15^{th} two-hour period was conducted at 22:00–23:00. The orange dotted one represents the 2^{nd} two-hour, 4^{th} two-hour, 6^{th} two-hour, etc., and the 15^{th} two-hour was conducted at 08:00–9:00. This method can guarantee the validity and integrity of data acquisition and avoid interferences caused by special holidays or accidents.

3.2. Data Processing. The path people choose to reach the stairs is the key to determining passengers' travel distance within the platform. Research shows that the location of platform entrances and exits has a significant impact on the distribution of passenger flow. An entrance will be crowded

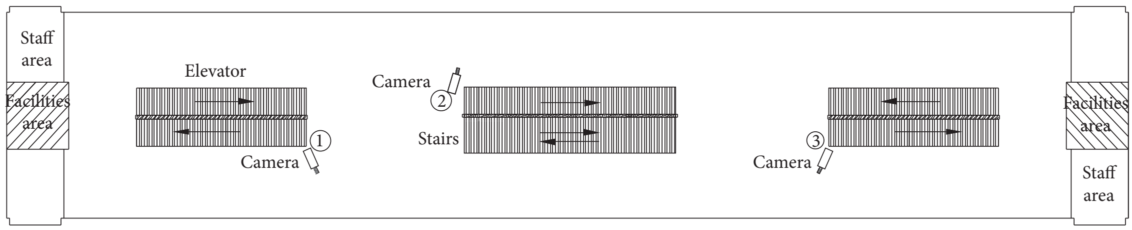

Figure 5: Data acquisition.

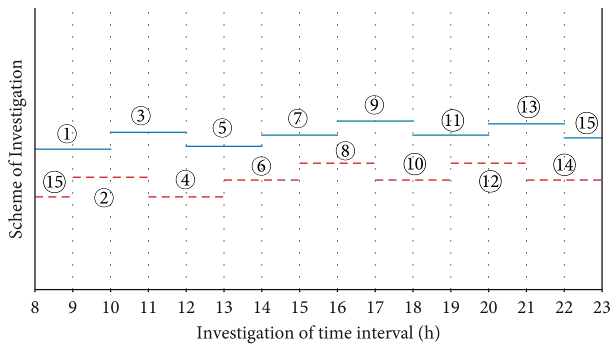

Figure 6: Survey time arrangement.

where there is only one entrance at the end. Thus, the dispersal of passengers will show a negative exponential distribution, whereas a station with multiple entrances and exits has a more even distribution of passengers, which conforms to a normal distribution, as shown in Figure 7. The stairs and escalators for entering and exiting are arranged on both sides and the middle of the platform. The majority of passengers can choose to leave the platform at the nearest exit, where the walking distance of the passengers leaving the platform is mainly at a medium length (30–60 m), while the walking distance at both ends is lower.

We asked the following questions: Does the walking time of passengers leaving the platform fluctuate at different times of the day? Will the passenger volumes during on- and off-peak hours affect the time required for passengers to leave the station? Does time spent differ when passengers carry different pieces of luggage? In response to these questions, the survey data for tracking passenger departure times and mapping the changes in departure times throughout the day was plotted, shown in Figure 8. The typical double peak change is "commuter passenger flow" and the peak time overlaps with peak passenger flow at the day. This type of passenger walking time is largely affected by the volume on the platform, whilst the frequency of arrivals for business passengers is related to the schedule of high-speed trains; therefore, the number of passenger arrivals is evenly distributed throughout the day. As for traveling with luggage, the time consumption of this group does not follow a peak curve, shown as the yellow and green curves in Figure 6. Business passengers with large pieces of luggage will have more walking time than those with small pieces of luggage, where the time required to leave the platform is increased.

At around 09:00 and after 22:00, the passenger volumes inside the hub station reach the lowest levels of the day. Two thirds of the passengers carrying luggage were outbound passengers. With fewer passengers carrying luggage, other passengers will have more walking space, and the walking time will be shortened as the walking speed increases. It is therefore reasonable to divide passengers into different groups according to their luggage carried.

Data concerning passenger flow over 17 hours were obtained from Beikezhan Station during the period of 06: 00–23:00. However, it is unreasonable to use all of the data in the calculation. The purpose of this study is to establish a calculation model considering the actual passenger characteristics; thus, to select periods where passenger behaviors are more distinct is reasonable, and using the data of more representative periods to study passenger characteristics is thereby a reasonable and practical method. The total number of passengers getting on and off during the 17 hours within the operation time could thus be obtained, and the passenger volumes changed with time when peak and off-peak volumes appeared. Peak hours account for at least 1/4 of the total 17 hours in the day, during which the space need is different from that of the passenger flow during the off-peak hours, so the model was applied to both peak hours and off-peak hours. The way we selected the representative periods was to use the volumes gained by analyzing and clustering the 17 passenger flows.

The k-means algorithm is a clustering algorithm for unsupervised learning. Its purpose is to cluster data according to the characteristics implied by the data itself [26]. Here, the clustering of passenger flows was performed by k-means clustering, and the clustering result output is shown as Figure 9. The determination of the number of cluster categories, k, is shown by a silhouette coefficient. The silhouette coefficient combines the cohesion and separation of clusters to evaluate the effect of clustering. The value is between approximately −1 to 1, and the larger the value, the better the clustering effect. The specific calculation method is as follows: since k is used to classify the operating hours of a day by passenger flow, it was not set to be large. By enumeration, we let k run from 2 to 15, repeating k-means several times for each k value (thereby avoiding a local optimal) and calculating the average contour coefficient of the current k value. Finally, the k value corresponding to the value with the largest contour coefficient was selected as the final number of clusters $k = 4$, shown in Figure 9(a). The full-day time pooling state diagram under $k = 2$, 3, 4, and 5 was output sequentially, as shown in Figure 9(b). It can be seen that when $k = 4$, the agglomeration classification is more representative.

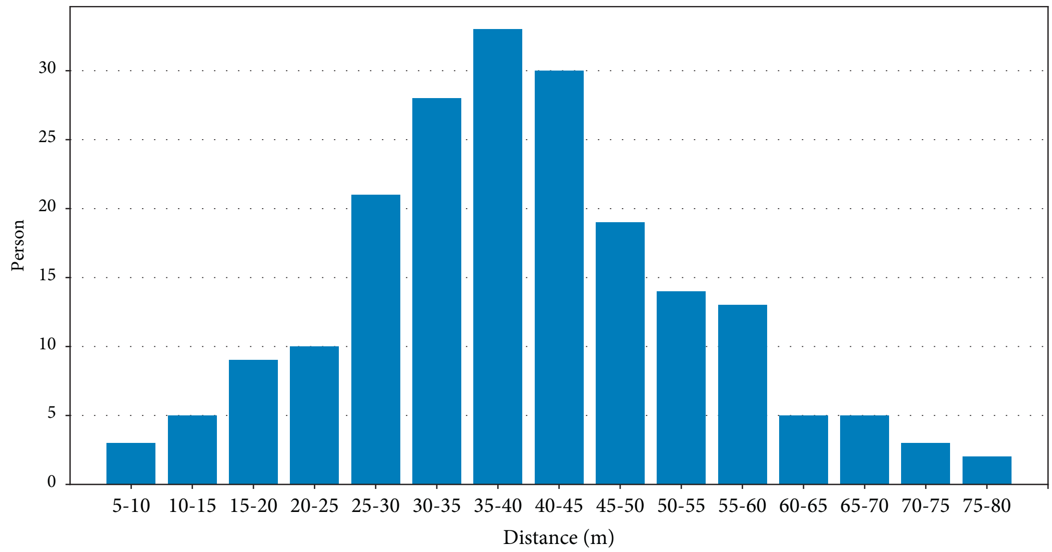

Figure 7: Movement distance of passengers leaving platform.

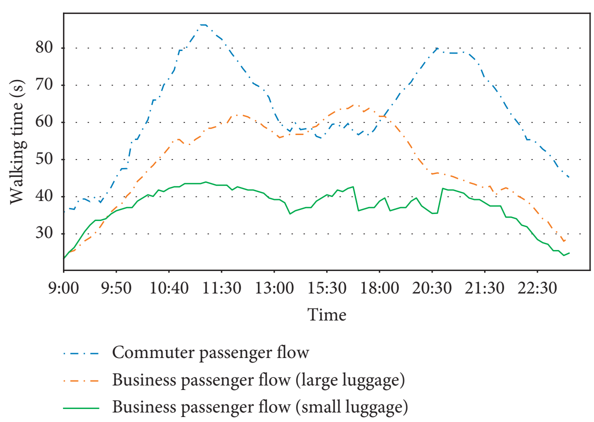

Figure 8: Walking time of passenger flows leaving the platform.

In the initial state of clustering, the data collected within the 17 hours were sorted in the order of 06:00–23:00. So, after determining $k = 4$, the representative four time periods needed to be found. According to the graph with the contour coefficient equal to 4 in Figure 9(b), we picked out the morning time of the day to be 08:00–09:00, the noon time to be 11:00–12:00, the afternoon to be 18:00–19:00, and the evening to be 21:00–22:00. These four time periods not only coincide with the peak hours of operation, but also include the off-peak period and comply with the presets of this paper for the site study period. Therefore, these four time periods were selected from the survey data to verify the model.

4. Results and Discussion

According to the model construction and behavior analysis of the passenger groups, combined with the results of the data processing, the passengers on the platform were classified. As shown in Table 2, the platform passengers were divided into three categories according to the size of their luggage. For passengers with no luggage or small carry-on pieces, a design value of 0.5 m^2/person can meet their space demands [27]. Meanwhile, as these passengers are free from luggage, their movement is not restricted, and changes are more obvious. This is shown in two patterns: one is that some passengers leave the platform first, whilst others tend to leave after the previous ones. Speed is the index to quantitatively describe these two patterns. Passengers without luggage or those carrying small pieces of baggage were further divided into G_1 and G_2, corresponding to the two types of moving behaviors shown above, respectively. The other two categories of passengers in Table 2 are defined as G_3 for passengers carrying suitcases or larger and G_4 for passengers carrying travel bags or more than one piece of luggage. Therefore, the cluster of passengers on the platform is $G[G_1, G_2, G_3, G_4]$. Next, according to the four types of passenger clusters, the collected data were sorted for the research over four hours, using representative periods obtained by the k-means clustering algorithm. The proportion of passenger clusters on the platform was calculated under the 24 train arrival times each hour at Beikezhan Station, which are denoted as $F[F_1, F_2, F_3, F_4, \cdots, F_{24}]$, as shown in Figure 10.

As can be seen from these figures, the total proportion of the four types of passenger groups on the platform at each moment in different research periods is about 100%, which indicates that all passengers on the platform are included in different groups; thus, this classification method is acceptable.

4.1. Passenger Group Characteristics and Dynamic Spatial Analysis. According to the timetable, 24 trains will arrive in one hour for the four typical periods of 08:00–09:00, 11:00–12:00, 18:00–19:00, and 21:00–22:00. Therefore, there are 24 datasets of passengers boarding and disembarking over each hour, and 96 datasets for the four periods, as shown in Figure 11. Then, passengers were divided into different types according to whether or not they had luggage and by the size of the luggage. The proportion of each passenger type for

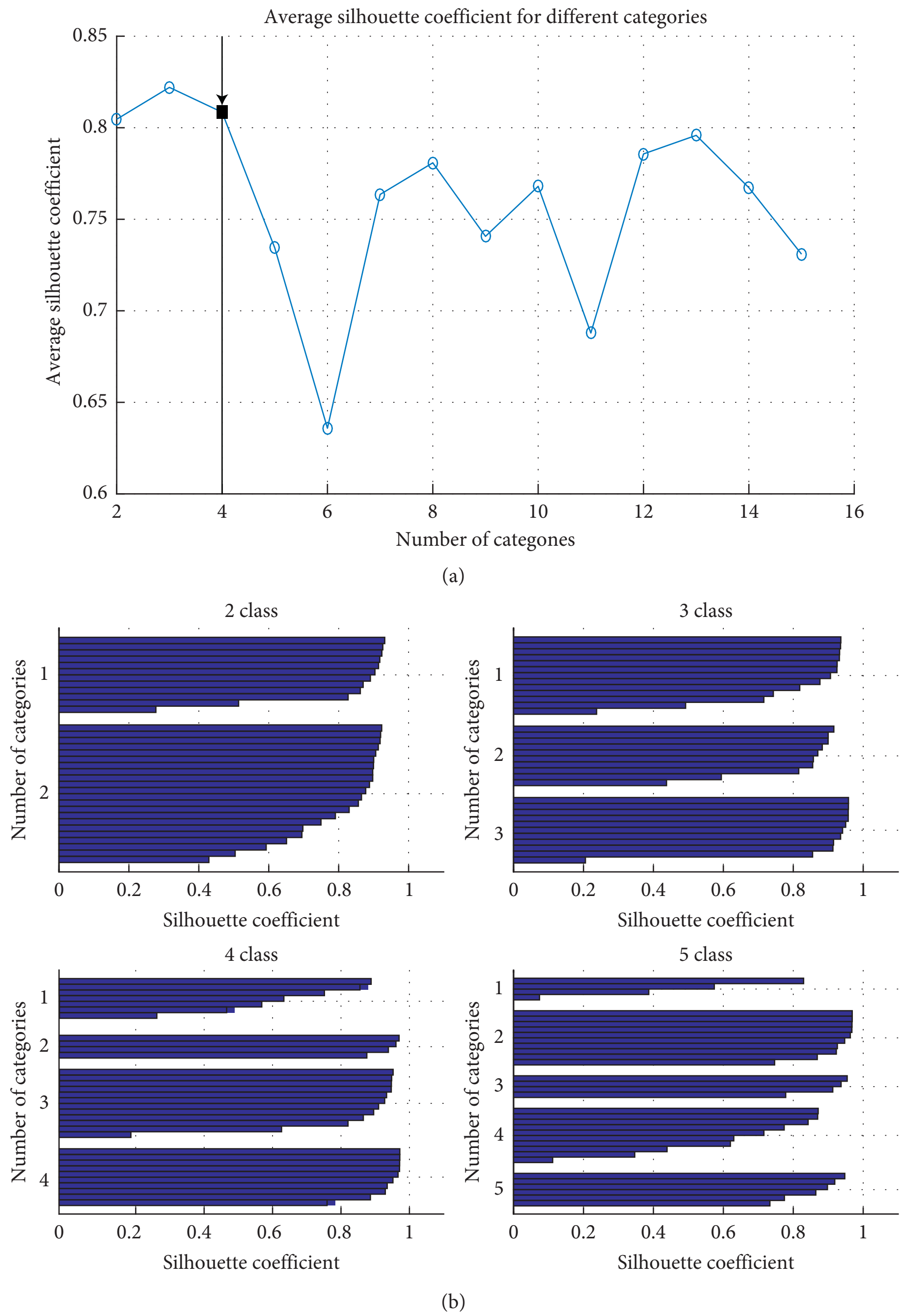

FIGURE 9: Determining the number of sample clusters.

each period is shown in Table 3. In the four passenger groups $G[G_1, G_2, G_3, G_4]$, each passenger's $g[p_1, p_2, \cdots, p_m]$ speed and walking distance exiting the platform was calculated by equations (5) and (9) using the relevant data. The flow of passengers on the platform was the set of $G[G_1, G_2, G_3, G_4]$, and the distribution of the speeds and walking distances meets a normal distribution here. The relationship between the traveling speed and density of passenger clusters is shown in Figure 12. It can be seen that the relationship between the passenger flow density and traveling speed of G_i classes differs. Due to individuals carrying baggage, the G_4 passenger group occupies more space, but walking will bring greater interference to the movement in other passenger groups. When the number of G_3 passenger group members increases, the density (includes the space of the luggage carried) will also increase, but the walking speed will significantly decrease. If the density is less than $1.0\,\mathrm{p/m^2}$, the walking speed can be kept to a comfortable pace. If the density is less than $1.3\,\mathrm{p/m^2}$, the passenger group can then walk at its own speed without being crowded. The walking speed of G_2 is slow, generally less than $0.8\,\mathrm{m/s}$, and there are more queues among the group members.

By combining equations (9) and (10), the dynamic space demand value of each passenger group can be calculated,

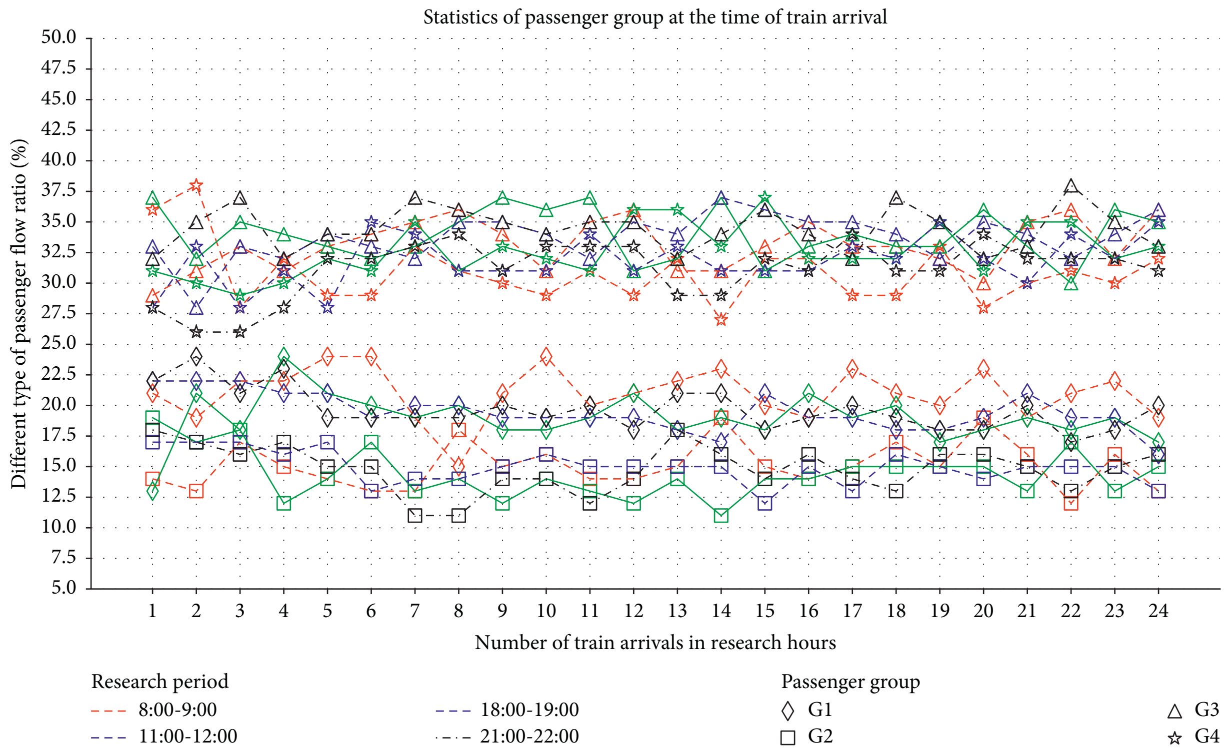

FIGURE 10: Statistics of train-to-station passenger flow at typical times over 4 hours.

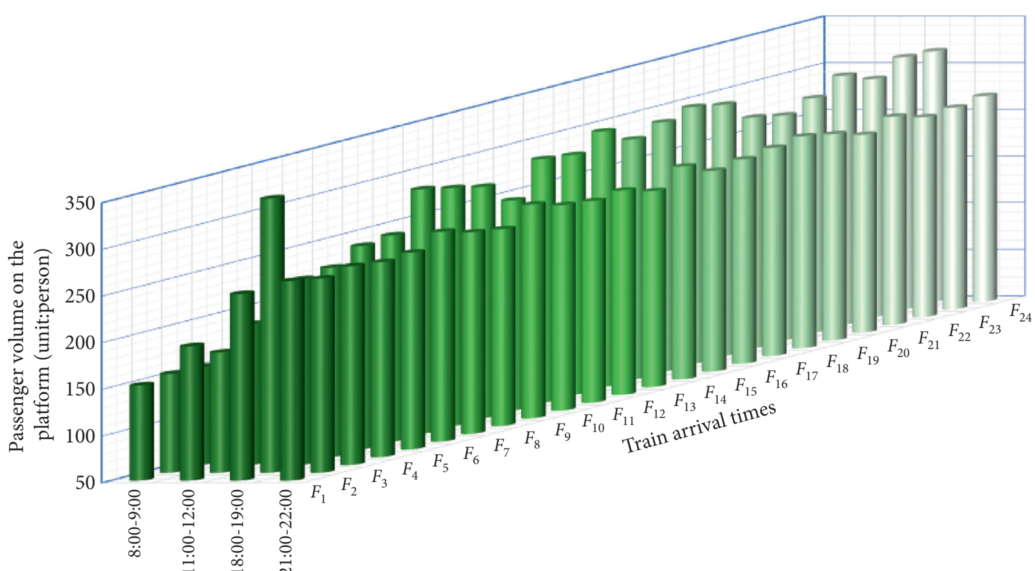

FIGURE 11: Number of passengers on the platform at the time of train arrival per hour.

that is, the area required by the passengers per second. The calculation results show the sorting of the dynamic space demand values (the calculation result shown in Figure 13), calculated by classifying the passengers consistent with the predicted values without the classification of passenger groups. The space demand values of the four types of passengers are within a certain range. G_2 belongs to a range of 9.5–13.5, where the pace is slow, takes more time to leave the platform, and is affected largely by the peak-hour passenger flow. Therefore, the space demand value is generally high and features fluctuations. However, the space demand value of G_1 is at a low level, because of its high pace and being luggage-free, which greatly shortens the dwelling time on the platform and reduces the space demand value, where the demand value range is 1.5–5.5. G_3 and G_4 differ in their sizes of the luggage carried. G_3 needs extra space with more

Table 3: Proportion of different types of passengers at different times.

Time		08:00–09:00	11:00–12:00	18:00–19:00	21:00–22:00
Arrival times (per hour)		F_1, F_2, F_3, F_4, F_5, F_6, F_7, F_8, F_9, F_{10}, F_{11}, F_{12}, F_{13}, F_{14}, F_{15}, F_{16}, F_{17}, F_{18}, F_{19}, F_{20}, F_{21}, F_{22}, F_{23}, and F_{24}			
Total number of passengers		3685	4559	7184	6419
Proportion	G_1	0.20	0.23	0.21	0.23
	G_2	0.19	0.17	0.19	0.17
	G_3	0.38	0.36	0.40	0.41
	G_4	0.23	0.24	0.20	0.19

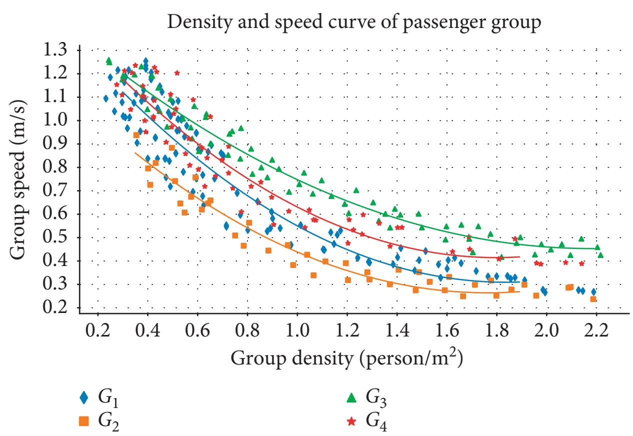

Figure 12: Density and speed distribution of passenger groups. The number of passengers with luggage accounted for 70% of the total number of passengers on the platform, and their walking speed was faster than the commuter flow. As such passengers are destined to catch a plane or high-speed train, their time consumption needs to be taken into account. Meanwhile, their movement will significantly affect the lower proportioned commuter flow, causing the latter's speed to reduce. Therefore, the walking speed of passenger groups G_1 and G_2 was lower than that of G_3 and G_4.

luggage. When leaving the platform, more space is needed on the platform per unit of time, and G_3 belongs to a range of 8.5–11.5. G_4 carries less luggage, and the demand value range is shifted to 6.5–10.5.

4.2. Model Application and Result Analysis. Combined with the parameter definition in Section 2, $E_i\{g[p_1, p_2, \cdots, p_m], G[G_1, G_2, \cdots, G_n], F[F_1, F_2, \cdots, F_c]\}$ is introduced, where $i = 1$, 2, 3, and 4 records the four typical periods. With $E_i\{g[p_1, p_2, \cdots p_m], G[G_1, G_2, G_3, G_4], F[F_1, F_2, \cdots F_{24}]\}$ being the states of the platform in this example, the size of the platform area may be solved using the spatiotemporal consumption model of the passenger clusters. Using the full sample data collected for four typical periods, time-space demand and required platform areas of all passenger groups were calculated in turn. The algorithm of this is shown below:

Step 1: Initialize the status of the platform, determine the walking space of passengers on the platform, and create control points which serve as boundary constraints of passengers entering or leaving the platform, within four typical hours, namely, 08:00–09:00, 11:00–12:00, 18:00–19:00, and 21:00–22:00, which were obtained through clustering at the data processing stage.

Step 2: In the first period, 08:00–9:00, for the first train arrival state, F_{11}, the pedestrian flow categories G_1, G_2, G_3, and G_4 are marked, and the frequency of occurrence of the categories a_1, a_2, a_3, and a_4 are counted. The platform size Z_{11} at the F_{11} moment is calculated according to the model and its parameters.

Step 3: Additionally, in the first period, if the second state F_{12} in the state set is updated, repeat Step 2 to calculate platform size Z_{12}.

Step 4: Determine the sizes of F_{12} versus F_{11}. If $Z_{11} > Z_{12}$, then Z_{12} is discarded and Z_{11} is reserved; otherwise, Z_{11} is discarded and Z_{12} is reserved. The reserved value is taken as the comparison object for the next step.

Step 5: Repeat Step 3 and Step 4 until the state $F_{1.24}$ is obtained, calculating the updates to get the optimal value Z_{1i} (trains arrive at an interval of approximately 2.5 mins; thus, arrival will repeat 24 times in one hour. Here, $F_1, F_2, \cdots F_{24}$ represent the 1st, 2nd, and 24th arrivals).

Step 6: Enter the second period 11:00–12:00, repeat Steps 2 to 5, and get the optimal value Z_{2j}.

Step 7: Enter the third period from 18:00 to 19:00, repeat Steps 2 to 5, and get the optimal value Z_{3k}.

Step 8: Enter the fourth period 21:00–22:00, repeat Step 2 to 5, and get the optimal value $Z_{4\gamma}$.

Step 9: The four local optimum values Z_{1i}, Z_{2j}, Z_{3k}, and $Z_{4\gamma}$ are judged, and the global optimum value Z is obtained.

The passenger walking area values under the 4 survey hours were calculated respectively using the optimization model constructed by the theory of spatiotemporal consumption. Trains arrive 24 times an hour, producing 24 passenger flow distributions. That means that passenger behavior varies each time a train arrives. The results for different arrivals per hour are shown in Figure 12. It can be seen that the values vary within the 96 arrivals. The area values are bigger during the 08:00–09:00 and 18:00–19:00 time slots than the 11:00–12:00 and 21:00–22:00 periods. Here, 11:00–12:00 and 21:00–22:00 are off-peak hours, whilst 08:00–9:00 and 18:00–19:00 are peak hours, where passenger volume increases largely, traveling passengers also maintain a more stable level, and passenger behavior changes greatly, where the proportion of passengers carrying luggage is higher, resulting in changes in the passenger walking speed.

The difference between the minimum and maximum platform areas required, divided by the minimum, is the fluctuation ratio, as shown by the green curve in Figure 14. This fluctuation ratio shows the space demand changes at two arrivalperiods. The greater the ratio, the greater the

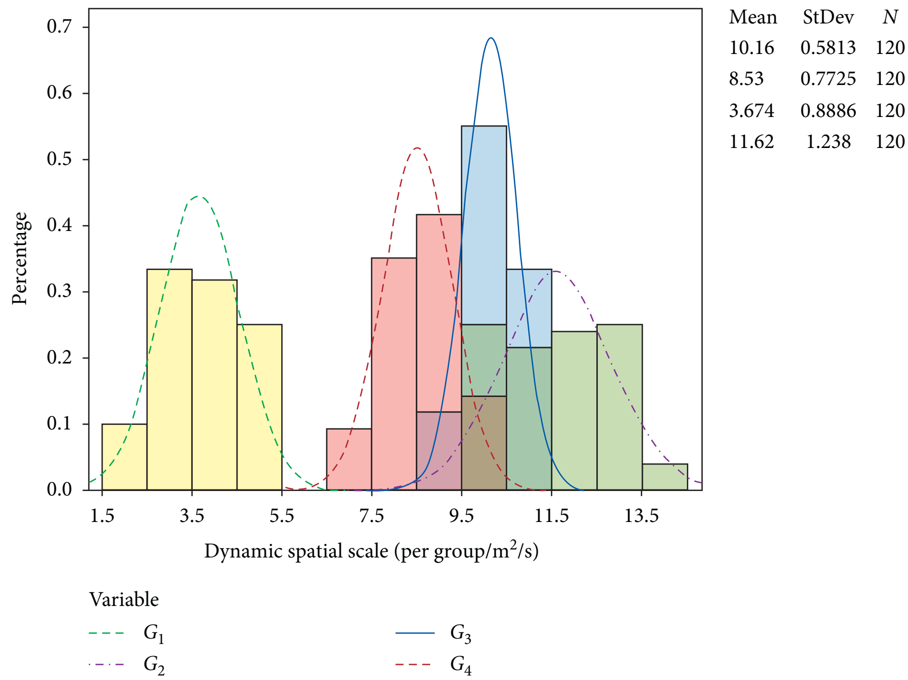

FIGURE 13: Dynamic spatial demands of different types of passenger groups.

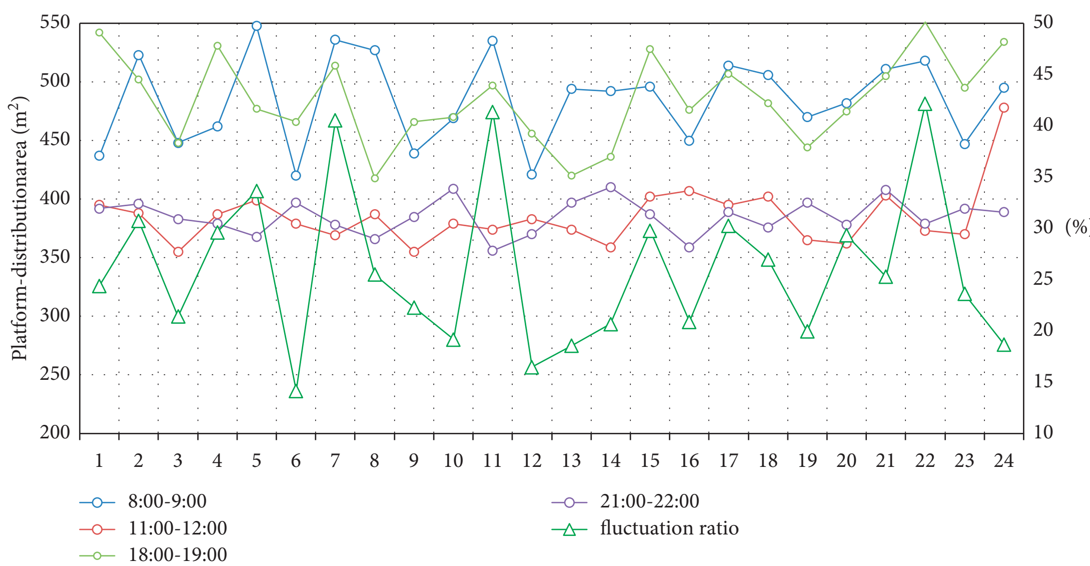

FIGURE 14: Scale of distribution area at different times.

change of passenger characteristics and thus the greater the impact on the determination of platform area, that is, the individual characteristics of passengers cannot be ignored. The average ratio calculated in this study was 27%; therefore, it is necessary to classify passengers on the platform by their behavior characteristics.

In this study, passenger groups G_1, G_2, G_3, and G_4 all appeared, and G_3 and G_4 with luggage appeared more frequently during the peak hours of 08:00–09:00 and 18: 00–19:00. The sum of these two is more than 35%; thus, the area occupied by luggage carried within groups G_3 and G_4 cannot be ignored. According to the values of the different dynamic space demands, the average demand value of the four passenger groups at different times has been obtained, as shown in Table 4. During the peak hours of 08:00–9:00 and 18:00–19:00, groups G_3 and G_4 have a significant impact on the platform size, and their walking areas are 103 m^2 and 122 m^2, respectively. During the off-peak periods of 11: 00–12:00 and 21:00–22:00, the total number of passengers decreased, resulting in a decrease in the walking area needed. The average area required for these four passenger groups is approximately 93 m^2. With a larger space demand, the result

Table 4: Proportion of different passenger groups and the average area demand of them.

Passenger group	08:00–09:00		11:00–12:00		18:00–19:00		21:00–22:00	
	Ratio (%)	Average area demand (m^2)	Ratio (%)	Average area demand (m^2)	Ratio (%)	Average area demand (m^2)	Ratio (%)	Average area demand (m^2)
G_1	0.22	85.64	0.25	64.69	0.21	92.42	0.27	79.88
G_2	0.14	92.45	0.10	71.25	0.19	102.69	0.08	86.25
G_3	0.43	103.91	0.53	93.01	0.37	114.92	0.46	84.37
G_4	0.21	122.25	0.12	93.75	0.23	136.11	0.19	85.41

of peak hours is larger than that of off-peak hours. As shown in Figure 13, the average platform area during peak hours is 489 m^2, whilst the area during off-peak hours is 375 m^2.

5. Conclusions

"Code of Design of Metro" offers a general calculation method for station platform size of urban rail transit, which is convenient to designers. However, passengers with luggage have different walking speed and space requirement from the ones without luggage; therefore, with the same ridership, stations mainly serving for passengers with luggage (e.g., transport hub stations) may need larger space than the general ones. Consequently, these stations need specific methods to calculate the platform size.

For filling this gap, this study proposed a spatiotemporal consumption-based model to calculate station platform model. We conducted an on-site investigation in Beikezhan Station which is a transport hub station of Xi'an Metro to validate the claims and the proposed model in this study. Data show that more than 70% passengers bring luggage in the hub station. And four typical time periods (morning: 08:00–09:00; noon: 11:00–12:00; afternoon: 18:00–19:00; evening: 21:00–22:00) are chosen in accordance with passenger flow features for further analysis. For the passengers appearing in these periods, they are classified as four groups (i.e., passengers without luggage, passengers with luggage covering an area of 0.25 m^2 or 0.5 m^2). Spatiotemporal consumption values are calculated using our model. Results showed that passengers' area demand reached a peak at afternoon period, which is critical for the demand of platform area. Based on this finding, the demand of Beikezhan Station platform area is up to 550 m^2 which is larger than the design one. Besides, sum of the average platform area required by passenger groups with luggage was approximately 1.2 times greater than that of groups without luggage. This result supports our claim that the difference brought by luggage variation could not be ignored. Classifying passengers according to the luggage carried, showed to be reliable and beneficial to the analysis of passenger group behavior.

Compared with previous research, this study formulated a station platform size calculation model considering dynamic space-time demand and the differences between passengers with and without luggage. It provides an accurate method to calculate station platform size. However, several assumptions were applied in this study. For example, the space occupied by an individual was assumed to be an ellipse, this is valid for passengers who do not carry luggage, but this condition needs further consideration if the passenger is carrying large pieces of luggage such as a lever case. In addition, there was a limitation to classify passengers by their luggage, whereas other factors could affect the area occupied by individuals, including age and gender. Therefore, further research on passenger group classifications is required.

Data Availability

The passenger flow data of urban rail transit platform used to support the findings of this study were supplied by Xi'an Railway Administration and Xi'an Metro Operating Company under license and so cannot be made freely available. Requests for access to these data should be made to the above two departments (+86) 029-89093123).

Conflicts of Interest

The authors declare that there are no conflicts of interest regarding the publication of this paper.

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