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Article

Spatial Flow Estimation Method Combining Space Syntax and Pedestrian Origin–Destination for Architectural Design Stage

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Abstract

Building spatial flow management is a critical link in ensuring the safe and efficient operation of spaces. Overcrowding in such spaces is likely to trigger a series of negative impacts, including delays and potential safety hazards. In this paper, we use the spatial flow estimation method to identify the future high-utilization space in the architectural design stage, so as to optimize the design scheme at the source and effectively alleviate the hidden danger of over-saturation of spatial flow in super high-rise buildings and transportation hubs. Firstly, the influencing factors of spatial flow are deeply analyzed in terms of the spatial structure and pedestrian demand based on fine microscopic simulation data of building pedestrians. Then, a space utilization intensity index is designed by introducing the visual integration degree of space syntax and the definition method of origin–destination (OD) influence scope considering obstacle derouting. Furthermore, the spatial flow is estimated based on the space utilization intensity index using regression analysis. Finally, taking the basement 1 floor of the Shenzhen Bay Super Headquarters Base C Tower connected with the metro as an example, the effectiveness of the proposed method is verified. The results show that the MAPE is 26%.

Keywords: spatial structure; view integration; pedestrian simulation; regression analysis

1. Introduction

In the field of architecture, "spatial flow" is a core concept, which mainly refers to the total number of pedestrians passing through a specific area inside or around a building within a given time period. It is not only a key indicator for measuring the activity level of building usage, but also a core factor influencing architectural functional design, spatial layout, safety evacuation, and commercial value. At present, Chinese architecture presents the complex characteristics of large volume and comprehensive function, strong passenger flow adsorption capacity, and obvious pedestrian flow aggregation phenomena. As of 2024, there are more than 900 super high-rise buildings over 200 meters in China, of which 212 are in Shenzhen, ranking first in the world. In super high-rise complex buildings, the phenomenon of human flow agglomeration caused by the morning and evening peaks is more obvious, especially in space areas such as important connecting passages and elevator waiting areas. For example, Shenzhen Ping An Financial Center covers an area of about 30,000 square meters, with a total construction area of more than 600,000 square meters. Its weekday pedestrian flow is as high as 62,000 people, the waiting time in the elevator area often exceeds 15 minutes, the per capita space is less than 0.6 square meters, far lower than the 1.5–3.0 square meters recommended by the "Store Building Design Code," and the space is seriously saturated.

At the same time, some buildings, such as transportation hubs and convention and exhibition centers, will also cause the agglomeration of people due to their functional characteristics, easily creating a bottleneck effect. In terms of Shenzhen as a whole, in 2024, the city's urban rail transit passenger traffic reached 11.88 million passengers in a single day, and the total number of passengers in the whole year reached 3.1 billion, both hitting a record high. As an important transportation hub in South China, Shenzhen North High-speed Railway Station registered more than 150 million passenger trips in 2024. In peak periods of passenger flow such as Spring Festival travel and holidays, up to 350,000 passengers can be recorded daily. High-density pedestrian flow leads to long-term saturation of channel space, and traffic efficiency is significantly affected. At the same time, Chegongmiao Subway Station, as a transfer station of Line 4 of Shenzhen Metro, has an average daily passenger flow of 230,000 people on working days, about 40% of which is accounted for by the passenger flow in and out of the station in the morning peak. Traffic in the station is slow, which affects the passengers' travel experience and also entails safety risks.

If an emergency occurs, evacuation will be very difficult. The building space is oversaturated, which causes a series of negative effects such as delays and safety risks. In the face of this phenomenon, national policy is systematically encouraging stakeholders to identify high building utilization areas, in order to locate and eliminate space bottleneck risks, and construct a safe and efficient building space utilization system. The Security Commission Office of The State Council clearly pointed out in the "Notice on Further Strengthening the Safety Management of Personnel Gathering in Public Places" that public places have the characteristics of high crowd gathering, strong mobility, high burst, and many accidental factors, so it is necessary to strengthen the monitoring of human flow and carry out safety risk assessments. Considering that human flow is an important indicator of building space utilization, and architectural design is one of the main influencing factors thereof, the calculation of spatial human flow in advance through scientific methods in the architectural design stage, with the aim of identifying the high utilization space of the building, and optimizing and adjusting the design scheme accordingly to alleviate the hidden danger of space supersaturation from the source, has become an urgent problem to be solved in current architectural design research.

In this study, we use fine micro-simulation data of building pedestrians for in-depth analysis of the influence of building space structure and pedestrian demand on pedestrian flow through the corresponding parameters of building space syntax and the proposed method of origin–destination (OD) influence range definition considering obstacle derouting. We then design a space utilization intensity index considering both approaches. Based on this, the spatial pedestrian flow is estimated using regression analysis.

The rest of this paper is structured as follows: Section 2 reviews the relevant literature; Section 3 describes the proposed building space flow estimation method, the data used, and their acquisition approaches; Section 4 verifies the proposed method through a case study of the basement 1 floor of the Shenzhen Bay Super Headquarters Base C Tower, and discusses its effectiveness in depth; Section 5 summarizes the research work of this paper and puts forward future research directions.

2. Literature Review

In recent years, with the increasing shortage of urban space resources and the diversification of building functions, the quantification and evaluation of space utilization has become a research hotspot. For the quantitative assessment of space use, existing studies mainly focus on the field of method research. In the early stages of research, scholars generally believed that the physical form of space itself was the fundamental factor determining the use of space. Therefore, research focused on the structural properties of architectural space and mainly used tools such as graph theory and space syntax to analyze the potential relationship between spatial structure and space utilization from a static perspective. The space syntax theory proposed by Hillier and Hanson [1] laid the foundation for this field, emphasizing the idea that space organization can guide human flow through invisible mechanisms. Based on this theory, Ye Junfang [2] pointed out that the topological structure property of a space system directly determines its potential utilization. Borba's research [3] proved that space syntax has more cost advantages than traditional models in identifying potential high-flow paths. In order to make up for the lack of micro-geometric representation of macro-topology, subsequent research began to introduce more elaborate modeling methods: Turner et al. [4] proposed a visual profile analysis (VGA) method for complex indoor environments, which quantifies visual depth and visual connectivity by discretizing the free plane into a line-of-sight grid, thus effectively predicting the visual perception preferences of pedestrians in scenes such as art museums. Song [5] et al. proposed a raster-based modeling method to express micro-scale geometric and semantic relationships in detail. Duan Jin et al. [6] also applied the syntactic model to the analysis of high-density urban form in China and verified the control effect of structural centrality on functional distribution. Zhou and Thill [7] constructed a directed graph model guided by the connection strength based on the functional key nodes in the urban transportation system, and used the network clustering method to identify the functional areas in the city. Wang Haofeng et al. [8] analyzed the spatial structure of a large-scale commercial complex using an axis diagram and pointed out the limitations of traditional syntax in dealing with multi-layer connections (such as elevators and escalators). Pont [9] et al. constructed an urban spatial typology model by quantifying the centrality of urban street networks and building density, which effectively reveals the differences in spatial organization of different macro-structures but, with this kind of method, it is difficult to capture specific high-intensity usage characteristics at the micro-scale. However, Ratti [10] criticized this method of abstractive space as a topological network, saying that it often leads to deviation due to researchers ignoring specific geometric and metric information when analyzing scenes with complex terrain or height differences. Although space syntax provides a powerful tool for spatial analysis, some specific information may be ignored because space is abstracted as a network of topological and geometric relations. Space syntax evaluates the efficiency of spatial organization from a static point of view but rarely considers dynamic changes such as traffic, which affects the accuracy of research.

In view of the shortcomings of the above static quantification methods, scholars have tried to introduce measured data to correct them. Eom and Suzuki [11] verified that the density of spatial structure was positively correlated with the distribution of pedestrian flow by introducing the actual observation data of central Tokyo; that is, the high-density spatial network often coincides with the high-intensity pedestrian flow agglomeration area in space. In their study of a commercial complex, Xu and Xia [12] innovated through the introduction of "functional space coefficient" and "spatial depth coefficient" structural indices in combination with the actual distribution characteristics of pedestrian flow, which effectively improved the accuracy of high-intensity spatial identification. In their study of transportation hubs, Danilina and Privezentseva [13] successfully identified three spatial utilization areas with different characteristics through clustering analysis of two types of heterogeneous data, "pedestrian flow" and "spatial axis length", which provided a composite model for functional zoning. Bao Xue and Lian Hua et al. [14] systematically partitioned and optimized campus walking space based on the characteristics of pedestrian flow agglomeration from the structural dimensions of accessibility and coordination degree. Sevtsuk [15] proposed a "network accessibility" model in the study of urban retail commercial locations and proved that after considering the destination attraction weight, the prediction accuracy of the model for commercial pedestrian flow was significantly better than that of traditional syntax. Fesenko and Szabo [16] revealed the coupling effects of structural elements such as visual depth and spatial continuity on pedestrian route choice behavior from the perspective of microphysical characteristics. The above studies show that spatial structure, as a physical carrier, defines the basis of space utilization through topological relations. Pedestrian flow, as a behavioral representation, reflects the actual representation of space utilization through dynamic density and trajectory.

With the rapid development of computer technology, simulation is increasingly used as a data acquisition and verification method in research on space utilization evaluation. Among relevant studies, dynamic simulation technology based on agent-based models has gradually become the research frontier. One such example is the social force model, which was proposed by Helbing and Molnar [17] in 1995. Based on the principle of Newtonian mechanics, pedestrians are regarded as self-actuated particles affected by "driving force," "repulsive force," and "attractive force." Although the model was proposed nearly 30 years ago, scholars still add visual and psychological factors to

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improve its applicability. Some scholars, such as Li et al. [18], have begun to modify the model by introducing perceptual factors such as visual field limitation. Choi et al. [19] used an agent-based model (ABM) to simulate crowd dynamics and combined it with sensitivity analysis to optimize parameters, in an effort to solve the lag of static analysis. Kirova and Markopoulou [20] used a data-driven ABM simulation to generate heat maps and predicted future space utilization trends by identifying high- and low-density areas. Lian et al. [21] constructed a multi-layer grid model to simulate crowd evacuation behavior under different exit layouts, and combined regional density and exit topology to realize the positioning of dynamic high-density areas, which verified the effectiveness of multi-grid modeling in dynamic emergency scenarios. In their study of museum scenes, Liu et al. [22] used microscopic simulation to confirm that only by comprehensively considering spatial connectivity and the microscopic behavior logic of pedestrians can accurate evaluation of residence time and circulation efficiency be achieved. However, although the above simulation techniques are relatively mature in terms of spatial representation at the physical level, there are still significant limitations in considering the complexity of pedestrian behavior when constructing simulation-based space efficiency evaluation systems. Most existing studies simplify pedestrians as "particles" that follow the rules of collision avoidance and focus on "hard indicators" such as evacuation time and traffic efficiency, while ignoring the differences between pedestrian behavior characteristics and travel purposes. For example, Moussaid et al. [23] compared video observation data of real crowds with simulation output results, and found that with a traditional model based on physical forces, it is difficult to reproduce the social interaction characteristics of groups such as "pedestrian side-by-side" that are ubiquitous in reality, resulting in significant deviations in prediction in complex scenes. Turner and Penn [24] endowed agents with "gaze analysis" in their early research and found that the motion trajectory of agents based on visual guidance highly coincides with the core integration degree of space syntax, which provides a dynamic verification for "spatial structure-guided behavior." Sime [25] performed a comparative analysis of actual evacuation cases and user psychology, and pointed out that the pure pursuit of engineering indicators such as "flow speed" is often out of line with the real sense of security of users, and cannot effectively characterize the stagnation and hesitation or subjective discomfort of pedestrians caused by environmental pressure. The study of Lo et al. [26], which is based on game theory, also shows that pedestrians have significant competition and cooperation psychology when choosing an exit, rather than simply following the physically shortest path. This means that, with the existing evaluation system, researchers have not been able to establish quantitative standards that accurately reflect the actual space use efficiency. Therefore, the successful integration of more explanatory micro-behavior and travel purpose logic into the simulation model, and the building of a scientific space efficiency evaluation system accordingly, would offer a key breakthrough to improving the quantification and classification accuracy of space use levels. This is also the core entry point of this study.

To sum up, the following research status conclusions are drawn:

(1) Spatial structure and pedestrian flow are the key influencing factors of space utilization.

Existing studies have shown that the utilization level of building space is largely affected by both spatial structure characteristics and pedestrian flow distribution. Research on space syntax shows that spaces with high integration easily become hotspots of pedestrian flow due to their good accessibility, and the attraction generated by the functional layout of buildings further strengthens the intensity of space utilization through pedestrian OD trajectories. Correspondingly, the areas at the edge of the spatial location have a lower utilization level. The spatial structure and pedestrian flow factors are coupled with each other, and the two factors work together to form a differentiated pattern of space utilization inside the building.

(2) The construction of a space efficiency evaluation system based on simulation has limitations in considering pedestrian behavior.

Although different scholars select different evaluation indicators in the construction of their evaluation systems, the pedestrian flow obtained based on the prediction method is essentially used as the source of simulation data which, in turn, is used as the input of the evaluation system, from which the effectiveness evaluation results are obtained. For the prediction of pedestrian flow in

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specific scenarios, researchers may ignore the limitations of pedestrian behavior characteristics; that is, they focus on oriented crowds with a clear OD and do not take into consideration the behavior patterns of exploratory crowds. The trajectory of an exploratory crowd in space is highly uncertain and its movement direction is affected by visual field information or other factors, which leads to deviation in spatial efficiency evaluation.

Therefore, in order to accurately describe the differences in spatial utilization levels within buildings, in this study, we relied on space syntax, considered pedestrian travel characteristics and travel purposes, and fused spatial structure and pedestrian flow information to propose a spatial utilization level classification method for building space, which provides a quantitative basis for spatial optimization and management decisions.

3. Research Methods and Data

This section is divided into six subsections. Section 3.1 introduces the two main influencing factors of building space flow: architectural spatial structure and OD demand. Sections 3.2 and 3.3 propose the quantitative impact indicators for building spatial structure and OD demand, respectively. Section 3.4 presents a comprehensive impact indicator for spatial flow based on the above two factors. Section 3.5 proposes a regression-analysis-based estimation method for building space flow, which takes the comprehensive impact indicator of spatial flow as the independent variable. Section 3.6 describes the data used in this study.

3.1. Analysis of Factors Influencing Spatial Flow

In this study, the degree of building space utilization was defined as the pedestrian traffic intensity in the internal area of the building, and a quantitative relationship between pedestrian flow per unit time and space area was constructed to analyze the spatial carrying efficiency and utilization degree of different regions.

3.1.1. The Demands of Origin–Destination

Pedestrian OD has a direct impact on space utilization by affecting the magnitude and main distribution of traffic. Pedestrian travel is highly goal-oriented. As the core element of pedestrian spatial activities, the distribution of pedestrian flow is mainly determined by the location distribution of OD pairs. At the same time, the OD volume also directly affects the volume of pedestrian flow. Therefore, the spatial distribution characteristics of OD not only directly determine the density and direction of passenger flow inside the building, but also have a direct and significant impact on the channel capacity and the traffic efficiency of transfer nodes through the superposition effect of flow in peak hours.

3.1.2. Spatial Structure

Spatial structure has an indirect effect on space utilization by affecting the path choices of pedestrians. While OD distribution specifies the general distribution of flow, in complex buildings such as large building complexes or transportation hubs, there is no single path for pedestrians from the starting point to the end point. Differences in route choices directly lead to differences in flow in different regions, and spatial structure is an important factor affecting this phenomenon. In other words, pedestrian route choice is affected by spatial structure. Bill Hillier, the founder of space syntax, believes that spatial structural elements inside buildings, such as moving line design, passage scale, and turning point, form an "implicit guidance" mechanism that can guide the direction of pedestrian flow without explicit identification through the transmission of visual information and the accumulation of behavioral inertia [1], thus affecting pedestrian spatial perception and action decision-making.

In summary, pedestrian OD and spatial structure constitute two key factors affecting architectural space utilization. Pedestrian OD determines the basic direction and scale of pedestrian flow, while spatial structure has a regulating effect on the specific path choice of pedestrian flow through the "implicit guidance" mechanism. In this section, we select scientific evaluation indicators based on pedestrian OD data and building spatial structure elements, respectively, to perform a

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quantitative analysis of building space utilization intensity and provide a theoretical basis for the identification and optimization of high-utilization space.

3.2. Influence Index of Spatial Flow Structure

By integrating "visual accessibility" and "spatial efficiency," the visual integration degree is more suitable for the quantitative needs of pedestrian behavior decision-making in this study in terms of analysis angle and applicability. In this study, pedestrian behavior decisions are influenced by the visual area. In other words, visual integration measures the potential of a space to attract arriving traffic. Therefore, in this section, we take visual integration as an index to quantify the influence of spatial structure on pedestrian flow for further analysis, referring to the research of space syntax and the work of VGA researcher Alasdair Turner on visual integration [4]. The specific calculation formula for grid $4s_i$ visual integration is as follows:

$$I(i)==\frac{\sum_{j=1}^{n-1}\log_2\left(\frac{j+2}{3}\right)}{(n-1)(\mathrm{MD_i}-1)} \quad (1)$$

where n represents the total number of grids in the system and MD_i represents the average depth of the grid i (mean depth); the specific calculation formula is

$$\mathrm{MD_i}=\frac{\sum_{j=1}^{n}\mathrm{Depth}_{i,j}}{n-1} \quad (2)$$

Equation 1 shows that the average depth index is normalized by the calculation of the view integration degree, so as to eliminate the influence caused by different topological structures and connection conditions in the system.

3.3. Spatial Traffic OD Impact Index

Obstacles interfere with the trajectory of pedestrians. The actual distribution of OD influence space is changed by pedestrians' autonomous detour behavior to the obstacles in their path. This effect is particularly significant in scenes with complex functions and dense pedestrian flow. In this paper, we propose a method to determine the pedestrian OD influence space considering obstacles to quantify the impact of pedestrian flow on space utilization. Pedestrians' obstacle avoidance behavior can be divided into two stages: "obstacle perception" and "obstacle detour."

3.3.1. Shape Analysis of Obstacle Perception

In the stage of obstacle perception, pedestrians cannot directly and accurately judge the specific shape of the obstacle through the surface of the obstacle in the field of vision. They can detour through the visual perception of the obstacle boundary, but the specific shape of the obstacle has little effect on the pedestrians' detour path. At the same time, in buildings such as shopping malls and traffic hubs, obstacles (walls, pillars, etc.) usually present a regular shape, and rectangular completion is more realistic. Therefore, we believe that pedestrians usually complete obstacles into rectangles according to what they see and then bypass them.

3.3.2. Considering the Definition of the Spatial Influence of Obstacle Detour

The effect of pedestrian OD on space mainly occurs at the stage of obstacle detour. For obstacles on the pedestrian path, in this study, we designed the minimum bounding rectangle to approximate the obstacles that had an impact on pedestrian walking. The minimum bounding rectangle refers to the rectangle on the plane that can completely contain the given point set and has the smallest area under the given conditions. For any obstacle in the plane, there is a set of vertices

$$P_i=\{s_j\in R^2 \mid j=1,2,3,\ldots,n\} \quad (3)$$

In pedestrian detour analysis, the known direction is determined by the starting point and end point D–O, in the direction of the minimum bounding rectangle longitudinal length; a unit vector is expressed as

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$$u_{OD}=\frac{\mathrm{D-O}}{\|\mathrm{D-O}\|} \tag{4}$$

At the same time, the orthogonal direction of the vector v_{OD} represents the transverse side length direction of the minimum bounding rectangle of the obstacle, which indicates the obstruction degree of the obstacle to the pedestrian, and generates the main detour cost.

Pedestrian OD influence space represents the spatial range affected by the trajectory when the pedestrian is affected by obstacles and produces detour behavior. As shown in FIG. 1, the pedestrian OD influence space was regarded as a rectangular space, which was affected by OD point coordinates, obstacle size, and pedestrian walking width. The four vertices of the rectangular influence space generated by the OD pair are represented by T_{OD_1}, T_{OD_2}, T_{OD_3}, T_{OD_4}, and the rectangular vertices of the pedestrian OD influence space can be expressed as follows:

$$T_{OD_1}:[X_O+(W_1+W)sin\theta,\ \mathrm{Y}_O+(W_1+W)cos\theta]$$
$$T_{OD_2}:[X_D+(W_1+W)sin\theta,\ \mathrm{Y}_D+(W_1+W)cos\theta]$$
$$T_{OD_3}:[X_O-(W_2+W)sin\theta,\ \mathrm{Y}_O-(W_2+W)cos\theta]$$
$$T_{OD_4}:[X_D-(W_2+W)sin\theta,\ \mathrm{Y}_D-(W_2+W)cos\theta]$$

Where $(X_O,Y_O)(X_D,Y_D)$ is the grid center coordinates of the starting point O and the ending point D, W is the fixed width of pedestrian walking, and θ is the horizontal angle between the vector u_{OD} and *X-axis*. W_1, W_2 represent the lateral width covered by the upper and lower part of the line where the obstacle is located; that is, the maximum projection difference between the upper and lower part of the obstacle vertex in the lateral direction. For the vertex set $P_i$of obstacle i, we define $P_{up}=\{\mathrm{s}_i\in P \mid v^{\mathrm{T}}(\mathrm{s}_i-O)\geq 0, i=1,2,3,\ldots,n\}$ and $P_{down}=\{\mathrm{s}_i\in P \mid v^{\mathrm{T}}(\mathrm{s}_i-O)<0, i=1,2,3,\ldots,n\}$, which represent the obstacle vertices located above and below the line OD, respectively. W_1, W_2 are calculated as follows:

$$W_1=\max_{\mathrm{s}_i\in P_{up}} v_{OD}{}^{\mathrm{T}}\mathrm{s}_i-\min_{\mathrm{s}_i\in P_{up}} v_{OD}{}^{\mathrm{T}}\mathrm{s}_i \tag{5}$$
$$W_2=\max_{\mathrm{s}_i\in P_{down}} v_{OD}{}^{\mathrm{T}}\mathrm{s}_i-\min_{\mathrm{s}_i\in P_{\mathrm{down}}} v_{OD}{}^{\mathrm{T}}\mathrm{s}_i \tag{6}$$

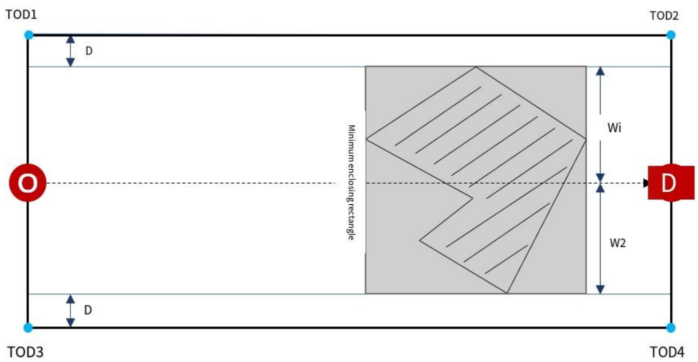

Figure 1. Schematic diagram of pedestrian OD influence space.

In the actual obstacle detour, pedestrians tend to choose the side with the shortest detour distance. Considering pedestrian detour preference, the OD line is used as the dividing line of OD influence space, the width of both sides is compared, and the smaller side is selected as the actual detour influence space, which is more in line with the real pedestrian path selection characteristics, thereby improving the accuracy of the measurement results.

3.4. Comprehensive Influence Index of Spatial Flow

The OD influence space can well quantify the influence range of pedestrian OD on space utilization. However, for the internal OD influence space, the distribution of grid utilization is not uniform, and pedestrians are still affected by spatial structure. To accurately depict the actual use of the characteristics of interior space, when we only depend on space form or pedestrian OD, the impact of a single index is often difficult to fully reflect space usage. Pedestrian OD reflects the actual travel demand and flow direction, while spatial form determines the visible accessibility of space and affects the distribution of pedestrian routes.

Therefore, based on the aforementioned pedestrian OD influence space determination method considering obstacles, in this study, we consider the joint influence of spatial structure and pedestrian OD on indoor space utilization, and design the grid utilization intensity (K) index $K(i)$ to represent the grid S_i utilization influence intensity of the grid cells in the space. The specific definition method is as follows:

$$K(i)=\sum_{j=1}^{n}\sum_{k=1}^{n} Q_{jk}\times \alpha_{ijk}\times \frac{I(i)}{I_{jk_{max}}} \quad (7)$$

where

Q_{jk} represents the amount of OD generated by the OD pair jk and reflects the intensity of the actual human flow in space.

α_{ijk} represents the coverage ratio of the grid s_i by the rectangular influence space generated by OD pair jk, and the value range is [0, 1].

$I(i)$ represents the integration value of visibility for grid s_i. $I_{jk_{max}}$ denotes the maximum visibility integration value among all grids within the OD influence space formed by j and k. It indicates that within the OD influence interval, spatial utilization exhibits uneven distribution due to the influence of spatial structure and visibility factors.Regions with higher visibility integration have a higher probability of being covered by pedestrian paths.

A grid using intensity structure characteristics and the space distribution characteristics of pedestrian flow coupling, so as to realize the quantitative characterization of indoor space utilization intensity, reveals the link between the flow rate distribution and the spatial form mechanism, achieving high recognition and data support for an optimized design.

3.5. Building Space Flow Estimation Based on Regression Analysis

In order to analyze the correlation degree of each index with the actual flow, in this subsection, we compare and analyze the actual flow, view integration, OD influence intensity, and grid utilization intensity normalized value with the grid number as the sequence. By drawing the scatter plot of the distribution in FIG. 2, and comparing and analyzing the scatter distribution and trend line, it can be seen that compared with the two indicators of view integration degree and OD influence intensity, the scatter distribution of raster utilization intensity is relatively concentrated, showing a similar change trend with the actual traffic. Specifically, the trend curve of raster utilization intensity is highly consistent with the actual traffic trend line in terms of fluctuation amplitude and direction, indicating that it has a stronger ability to explain the actual traffic. The Pearson correlation coefficient results show that the correlation coefficients between the actual pedestrian flow and the visual integration degree, OD influence intensity, and grid utilization intensity were –0.0011, 0.0917, and 0.4301, respectively, and grid utilization intensity shows a positive correlation with the actual pedestrian flow. Therefore, in this paper, we use the grid utilization intensity index to regression-fit the actual flow.

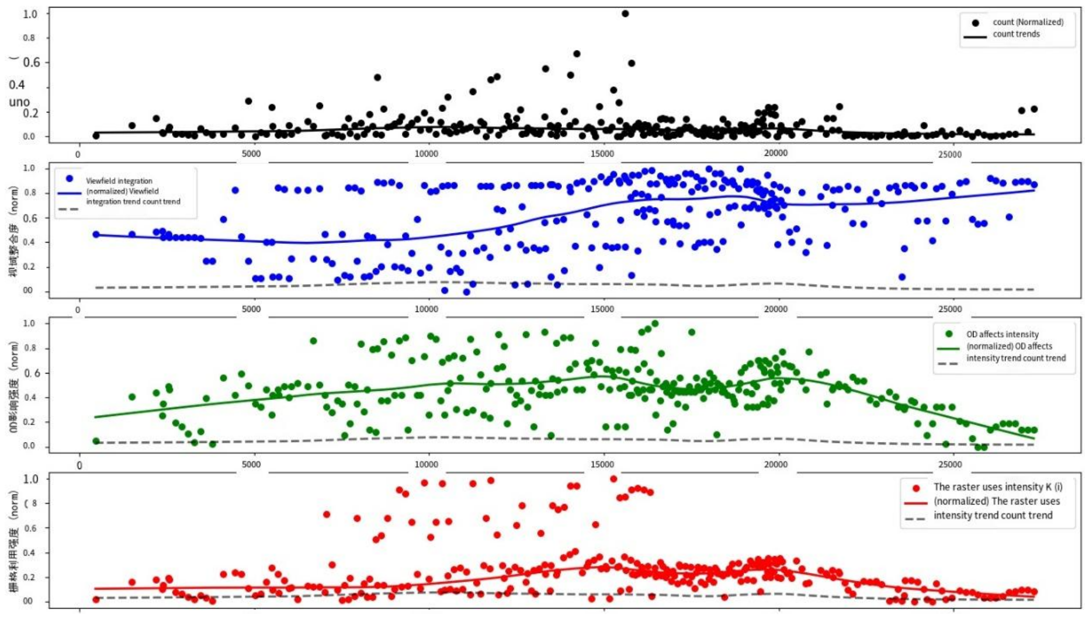

Figure 2. Comparison of scatter distribution and trend line.

3.6. Research Scope

Shenzhen Bay Super Headquarters Base is one of the key development areas of Shenzhen. It is positioned as "a typical representative of the ultimate status of the city in the global economic and industrial chain, and a functional center for Shenzhen to develop into a world-class city." Its goal is to become a landmark node, as part of a new generation of headquarters economic zones, which will allow Shenzhen to join the ranks of international cities. Its total land area is 117 hectares, the total development area is about 5.2 million square meters, and the employment population is about 300 thousand. The area will build a future urban model integrating a global headquarters gathering area, an urban cultural highland, an international exchange center, and a world-class coastal city area. Located in the core location of Shenzhen Bay Super Headquarters Base, Tower C is one of the super high-rise landmarks of the "Shenzhen Bay urban core" in the area. Tower C, shown in Figure 3, is the absolute center of Shenzhen Super Headquarters, representing the spirit of Shenzhen, and is a new window for the world to know the city. The total land area of the project is 36,268.61 square meters, and the floor area of the specified floor area ratio is 440,000 square meters. The use types include office (291,310 square meters), commercial (54,500 square meters), hotel (30,000 square meters), culture (44,000 square meters), municipal transportation (18,000 square meters, including municipal transportation facilities and a transfer distribution space area index of 10,500 square meters), postal branch (1500 square meters), and a property service room (690 square meters). Underground, there is an intersection of several urban and intercity rail lines, mainly including Shenzhen metro lines 9, 11, and deep inter-city (Shenzhen), whereas the ground buildings and traffic facilities together form a super-tall TOD synthesis of landmark towers. The first floor is connected to a shuttle bus depot, mezzanine B1 is connected to a taxi terminal, and floor B1 is connected to the subway station. This paper focuses on the negative floor connected to the subway, as shown in Fig.4 below.

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Figure 3. Design rendering of Tower C.

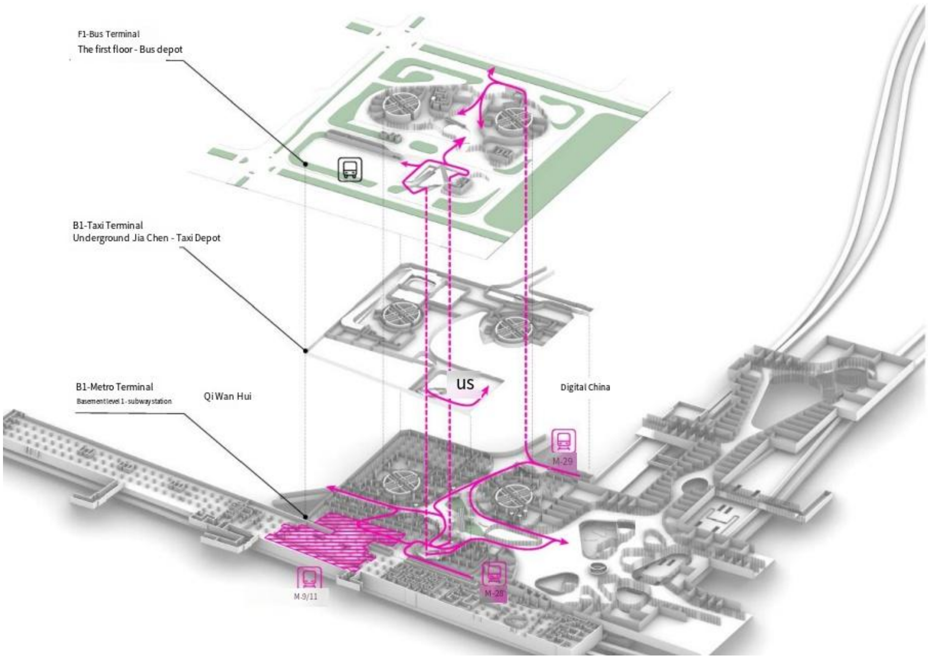

Figure 4. Schematic diagram of the first floor and B1 floor of Tower C.

4. Results and Discussion

4.1. Influence Index of Building Space Flow Structure

As a spatial structure index, the degree of view integration is used to measure the relative relationship between a certain grid and other grids. Under the assumption that pedestrians lack a clear global goal, the higher the visual integration degree, the stronger the guidance to pedestrians and the more likely it is for the grid to be passed; the flow is also greater, so space has a higher utilization degree. In order to verify the influence of spatial structure on pedestrian flow distribution, in this subsection, we consider horizon integration as an important representation of the spatial structure index from the aspects of both qualitative and quantitative influence on spatial structure.

4.1.1. Principles and Methods of the Experiment

Theoretically, when the distribution of points is sufficiently uniform and the travel volume between each OD pair is equal—that is, when each grid cell has the same probability of being the origin or destination—it can be considered that pedestrian flow distribution is only affected by spatial structure, which is consistent with the connotation of visual integration. In order to verify the effect of visual integration on pedestrian flow, in this study, we arranged OD points uniformly in the corridor space to simulate a balanced travel demand in the whole region. The denser the OD distribution, the stronger the ability of visual integration to describe the space utilization. By observing the distribution of areas with high values of visual integration and high values of flow, it can be considered that when the actual flow of areas with high visual integration is greater, spatial structure has a certain impact on the level of space utilization.

In this study, four groups of simulation experiments with density intervals of 35 m, 25 m, 15 m, and 10 m were set up, and OD points were uniformly distributed in the channel area, as shown in Figures 5–8. The density of OD points increases and gradually approaches the situation where pedestrian walking is completely determined by space. At the same time, in order to ensure comparability between different experiments, the experimental set up from any point to all others is constant, with the number of OD points set to two and the duration even being 15 minutes, as much as possible in the case of reduced congestion simulation under different layout density areas with high performance. The statistical grid is the line frequency as the actual pedestrian flow; the higher the frequency, the greater the flow, and the higher the levels of space utilization. Finally, the raster flow is normalized by 0–1, which allows the visualization results to better show changes in high-value areas.

In particular, considering that space edges, narrow channels, or poor accessibility usually generate and attract less traffic in actual situations, in this study, we appropriately reduce the number of OD points in such areas, so that the simulation is more in line with the real law of space use.

Figure 5. OD point layout diagram (35 m interval).

Figure 6. OD point layout diagram (25 m interval).

Figure 7. OD point layout diagram (interval 15 m).

Figure 8. OD point layout diagram (interval 10 m).

4.1.2. Qualitative Analysis of the Influence of Spatial Structure

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By processing and analyzing the simulation output, a comparison group diagram of traffic distribution and view integration under different OD point deployment densities is obtained, as shown in the following figure. By observing the changes in high-traffic grid distribution, it can be seen that with the increase in OD pair deployment density, the high-value grid area in the space gradually moves from global dispersion to central contraction, and the consistency between traffic distribution results and visual integration analysis results is stronger, as shown in Figures 9–13. Areas with higher visual integration showed higher flow levels, indicating that these locations had stronger visibility and reachability in the spatial structure, so it was easier to attract pedestrians to pass by, indicating that the spatial structure itself had a guiding effect on the flow. Thus, the important spatial structure factors influencing space utilization were verified from a qualitative perspective.

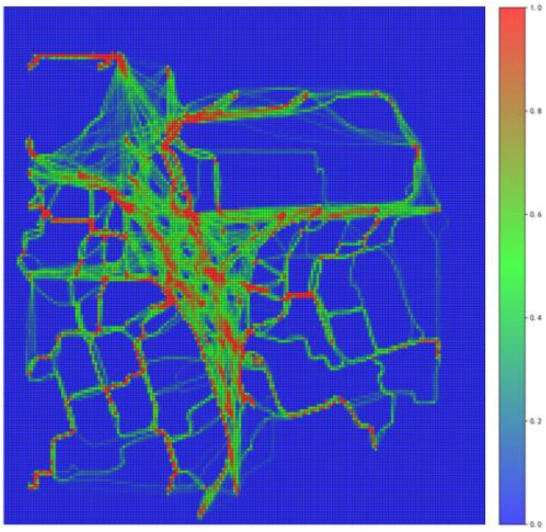

Figure 9. Flow distribution of OD layout with interval of 35 m.

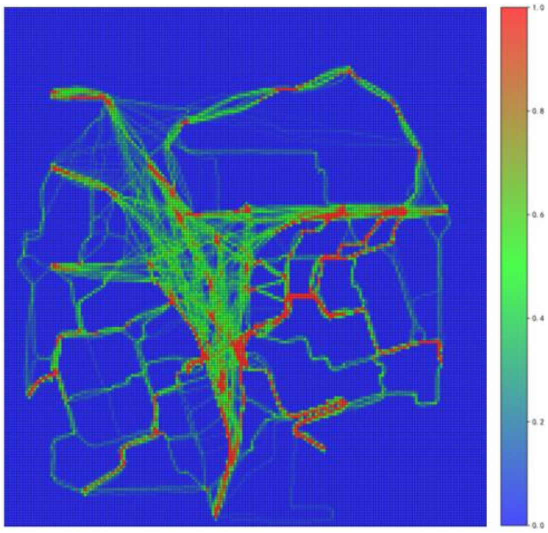

Figure 10. Flow distribution of OD layout with spacing of 25 m.

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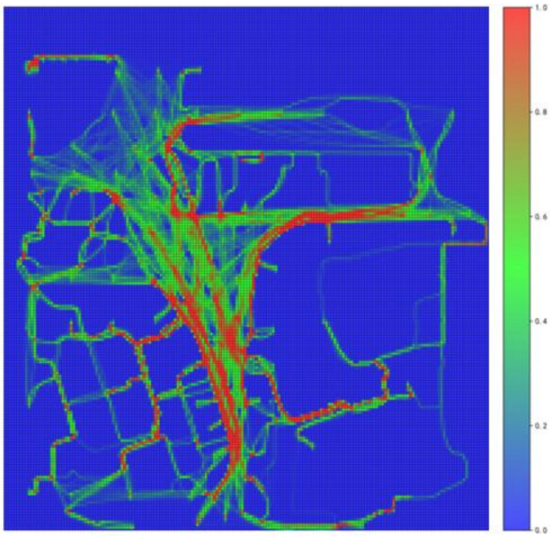
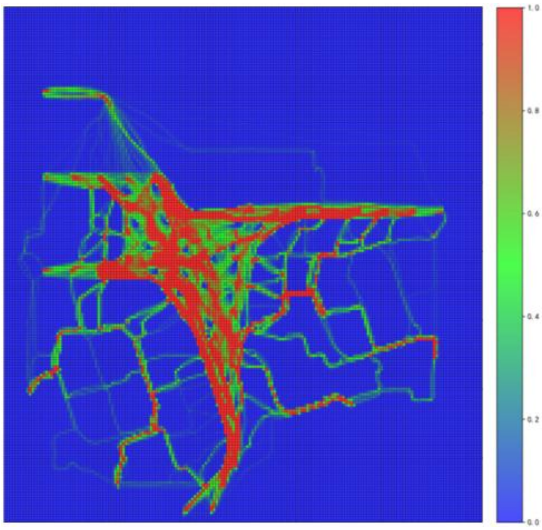


Figure 11. Flow distribution of OD deployment with interval of 15 m.



12. Flow distribution of OD deployment with interval of 10 m.

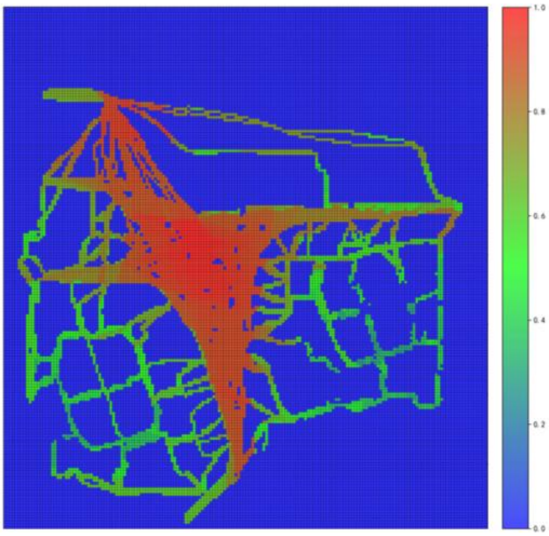


Figure 13. Integration analysis diagram.

(3) Quantitative analysis of the influence of spatial structure

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In order to quantitatively reveal the influence of spatial structure on pedestrian flow, in this subsection, we perform a correlation analysis on the experimental groups with different OD point spacings. The Pearson correlation coefficient can accurately measure the correlation degree between two variables when they are approximately continuous and the sample size is large, and the results have clear statistical interpretation and comparability. Therefore, we further carried out a Pearson correlation analysis between the degree of visual integration and the actual flow, and the data results are shown in Table 1. As can be seen from the table, with the increase in OD point distribution density, the Pearson correlation coefficient between variables showed a significant upward trend, from a weak positive correlation (0.2486) to a strong positive correlation (0.7056). The corresponding t-value increased from 2.867 to 9.807, and the standard error gradually decreased, and the overall significance, two-tailed significance, and one-tailed significance levels under all schemes were all equal (<0.0001), showing that there is a certain degree of positive correlation between variables, which is statistically significant. In other words, areas with higher visual integration tend to have higher flow levels and higher spatial utilization; that is, to some extent, spatial structure has an impact on spatial utilization.

Table 1. Results of Pearson correlation analysis.

Experimental Protocol	Pearson Correlation Coefficient	T-value	Overall Saliency	Two-tailed Saliency	Single-tail Saliency	Standard Error
OD Point Layout Spacing 35 m	0.2486	2.867	<0.0001	<0.0001	<0.0001	0.372
OD Point Layout Spacing 25 m	0.4561	6.841	<0.0001	<0.0001	<0.0001	0.139
OD Point Layout Spacing 15 m	0.5375	8.326	<0.0001	<0.0001	<0.0001	0.094
OD Point Layout Spacing 10 m	0.7056	9.807	<0.0001	<0.0001	<0.0001	0.072

4.2. OD Impact Index of Building Space Flow

4.2.1. Experimental Principles and Methods

Pedestrian OD is the direct source of flow in the spatial flow generation mechanism. In theory, when there is a quantitative increase in travel between two points, the local distribution of pedestrian OD will be obviously increased, thus affecting the use of space. Therefore, observing the impact of local OD on the overall flow pattern can be used to verify the direct driving effect of pedestrian OD on space utilization.

In this subsection, we look at pedestrian OD before and after the change in flow rate distribution mainly from two aspects in order to validate how pedestrian OD affects the use of space:

(1) Multiple OD pairs were set to test the rationality of the improved method of defining the space affected by pedestrian OD.

Keeping the space structure, grid division, and other simulation as invariable parameters, we randomly selected three OD pairs as the experimental object and examined the influence on space and visualization separately for each pair of OD points before and after the improvement in OD. The results are shown in Figure 4.4.3-1. In the simulation, the grids covered the statistical paths and the OD influence space.

In order to verify the rationality of the improved OD influence space, in this part, we quantified the improvement effect by designing two indicators: "accuracy" and "path raster proportion."

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Accuracy refers to the probability that the pedestrian path grid falls in the OD influence space and represents the ability of the OD influence space to contain the pedestrian path. The calculation method is as follows:

$$\text{Accuracy}=\frac{\text{Number of path grids falling within the influence space}}{\text{Total number of path grids}}$$

Path proportion refers to the proportion of path grids in the grids contained in OD influence space and represents the redundancy rate of OD influence space. The calculation method is as follows:

$$\text{Path ratio}=\frac{\text{Number of path grids falling within the influence space}}{\text{Total number of grids contained in the OD influence space}}$$

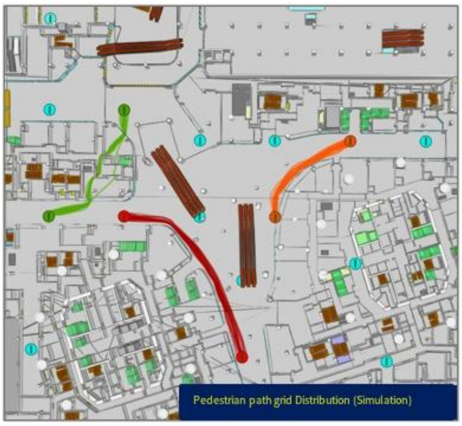

Figure 13. Grid distribution diagram of simulated pedestrian paths.

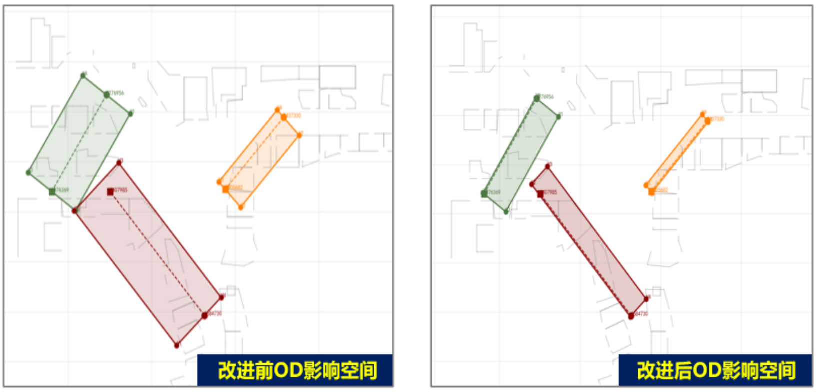

Figure 14. Comparison of pedestrian OD influence space before and after improvement.

(2) Different OD values are set for the same OD group to observe the changes in high traffic grid distribution.

In this part, the location and OD quantity of other OD pairs in the simulation scene were kept unchanged, and two points, A and B, were selected as the experimental object (as shown in Figure 15). The OD quantity was increased to 100, 200, and 300 to simulate a situation in which demand intensity gradually rises between the two points and observe whether the distribution of high-traffic grids and the overall space utilization have been adjusted on a large scale, so as to verify the influence of OD on space utilization.

Figure 15. Location map of points A and B in the simulation scene.

4.2.2. Improving the Rationality Analysis of Pedestrian OD Influence Space

The analysis results show that the improved OD influence space can more accurately capture the actual utilization of the local area by pedestrian travel and more fully describe the pedestrian path. Firstly, in terms of the proportion of path grids, the growth rate of the improved OD influence space is higher than 100% compared with that before improvement, which indicates that the improvement of the original definition method of OD influence space can effectively reduce the error of OD influence quantification. In addition, the analysis of the accuracy index shows that there is little difference in OD influence space accuracy before and after the improvement. Although the accuracy decreases slightly after the improvement, it is still at the level of more than 85%, indicating that most of the pedestrian path grids fall into the constructed OD influence space. Therefore, the improved definition method of OD influence space is reasonable to a certain extent. The specific data and effect diagram are shown in Table 2 and Figures 16–17.

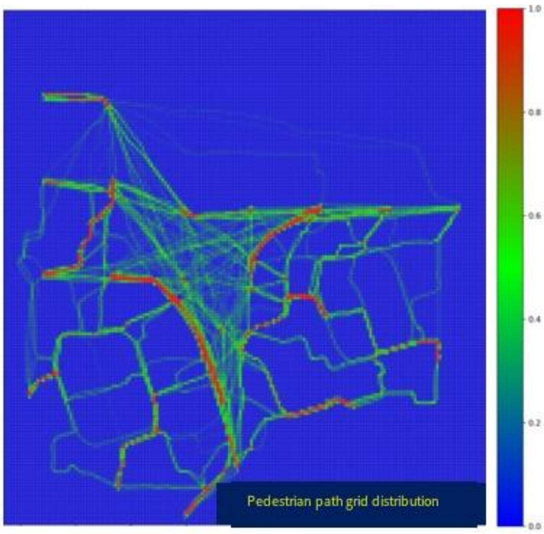

Figure 16. Actual pedestrian path distribution diagram.

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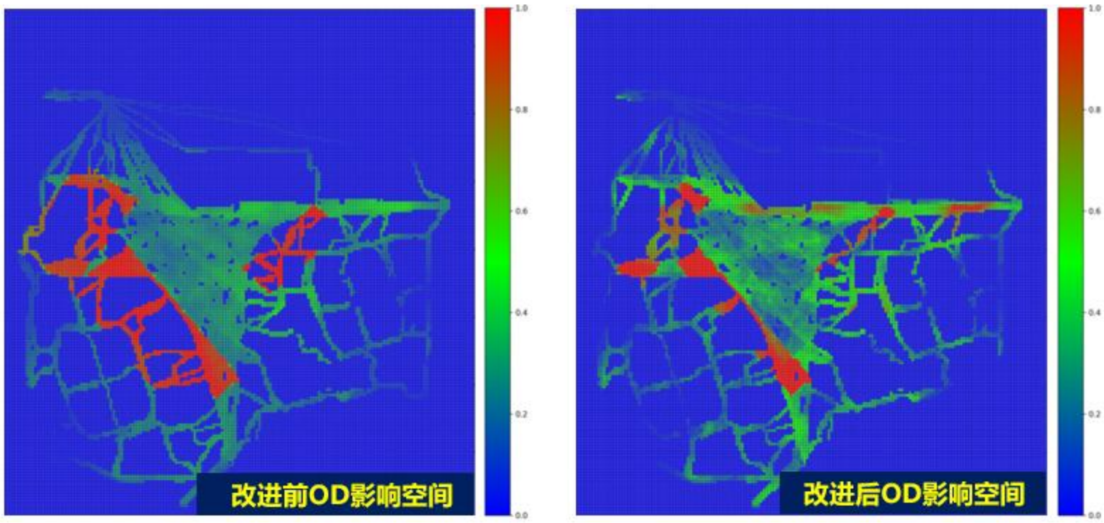

Figure 17. Comparison of quantization effect before and after improvement of OD influence space.

Table 2. Quantitative results of OD influence space before and after improvement.

OD Pair	OD Influence space	Path Raster count	Number of Path Grids that Fall inside the Influence Space	Influence Space Total Number of Grids	Accuracy	Percentage of Path Grids
OD1 (green)	Before	141	131	1047	92.91%	12.51%
	After		129	520	91.49%	24.81%
OD2 (red)	Before	247	223	1975	90.28%	11.29%
	After		216	849	87.45%	25.43%
OD3 (orange)	Before	124	110	805	88.71%	13.67%
	After		107	369	86.29%	28.98%

4.2.3. Pedestrian OD Impact Analysis

By observing the changes in traffic distribution, it can be seen that with the increase in OD between two points A and B, the flow in the local area connecting the two points increases significantly, and so does the space utilization degree, forming a clear high value band. However, the flow in other areas essentially remains stable; that is, there is no large-scale change in the flow distribution, and its change is mainly affected by the change in pedestrian OD at A and B, which verifies that pedestrian OD has a significant positive role in space utilization. The simulation output results were processed and analyzed, and a normalized actual flow visualization map was obtained as shown.

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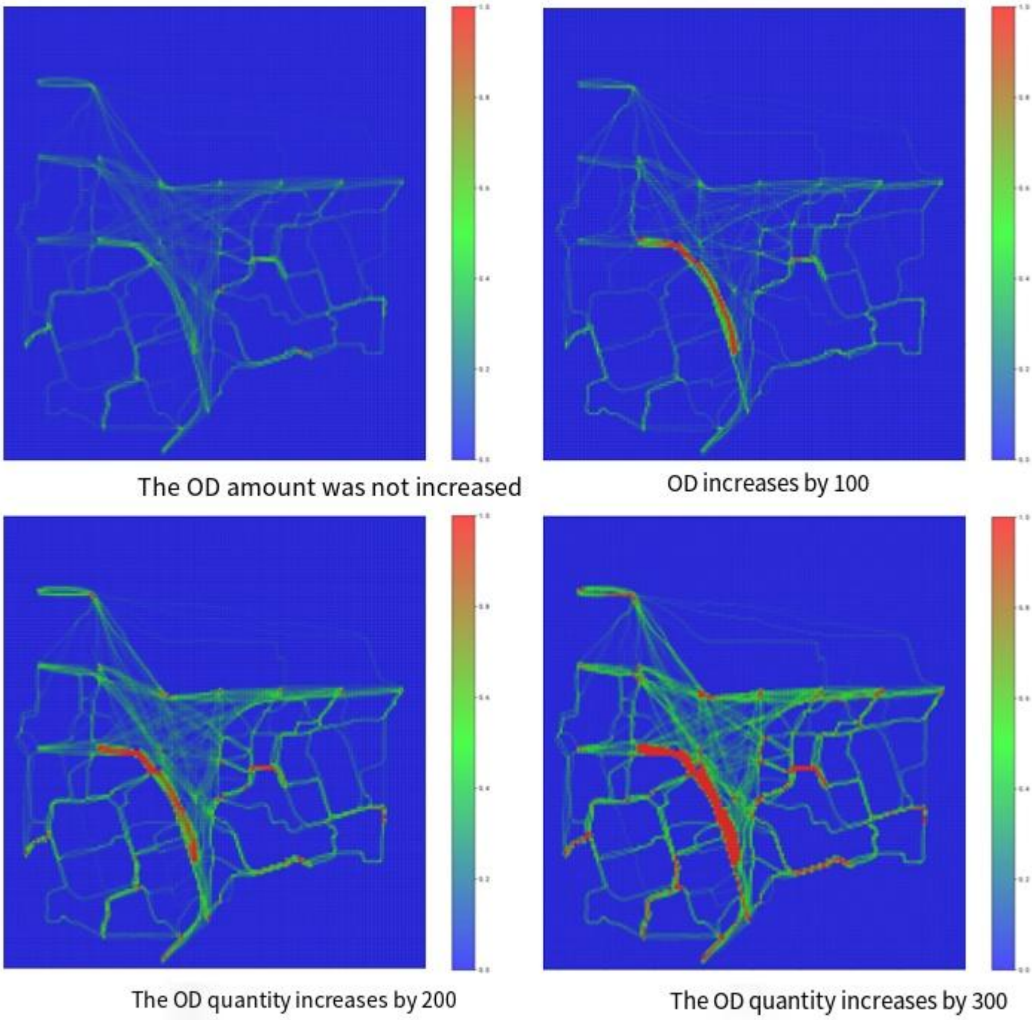

Figure 18. Flux distribution variation.

4.3. Comprehensive Impact Index of Building Space Flow

According to the OD influence space quantification method in 3.3.1, for two points A and B in the channel area in 3.3.2, the corresponding influence space rectangle was constructed, as shown in Figures 19–20, and the coordinates of four vertices were output at the same time. Then, the simulation results were processed, the distribution of pedestrian paths was analyzed, and the grids covered by pedestrian paths were counted. The results show that the OD influence AB interval contains grid 214, which falls in the direct path of OD influence space grid 209, accounting for 97.66%. In other words, most of the pedestrian path grids fall into the constructed OD influence space, indicating that the space division can accurately capture the actual utilization of local areas by pedestrian travel.

Figure 19. Schematic diagram of the OD influence space between the two points A and B.

Figure 20. Actual pedestrian trajectories at the two points A and B.

Firstly, we compared and selected the appropriate regression model to establish the mapping relationship between the grid utilization intensity and the actual pedestrian flow, and converted the grid utilization intensity value into the corresponding pedestrian flow value to reflect the association between the potential utilization degree of space and the actual pedestrian flow distribution. Then, referring to the relevant traffic classification standards, the flow results obtained by regression were divided into intervals, and the seed grids were obtained according to the different level thresholds, so as to describe the utilization degree and distribution differences of different grids.

4.4. Regression Analysis of Architectural Space Flow Calculation

In order to test the corresponding relationship between grid utilization intensity and actual human flow, and evaluate its ability to explain flow changes, we carried out a comparative study of regression models on the basis of the above correlation analysis, and compared and analyzed the explanatory ability of different models between flow and grid utilization intensity, so as to select the optimal regression fitting model. The data used in the regression analysis were from the simulation results of Tower C in Shenzhen Bay, and the OD matrix of simulation pedestrians was set by random generation. At the same time, the number of times each grid was passed by pedestrians was recorded as the actual flow.

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Figure 21. Mass motion pedestrian simulation diagram.

After cleaning the simulation data, 43,003 valid rasters were selected, including 9826 non-zero actual flow data and 9445 raster utilization intensity data. The results of the descriptive statistics show that the mean and standard deviation of actual traffic were 275.95 and 246.49, respectively. The mean of grid utilization intensity was 406.04, and the standard deviation was 210.25, reflecting that there were significant differences in human flow and utilization levels in different regions. In addition, the values of each control variable were in a reasonable range, and there were no obvious extreme outliers. The data quality thus met the needs of the subsequent model analysis.

The grid utilization intensity was taken as the independent variable, and the actual flow was taken as the dependent variable. The scatter distribution diagram is shown in Figure 22. By observing the distribution of scatter points, it can be seen that with the increase in grid utilization intensity, the actual flow value generally showed a monotonically increasing change trend. Therefore, in order to further characterize the functional relationship between the two, we decided to use a linear regression model, an exponential regression model, a power regression model, and a logarithmic regression model to fit and analyze the actual traffic, as shown in Figure 23. The correlation evaluation index (R^2), root mean square error (RMSE), mean absolute error (MAE), and mean absolute percentage error (MAPE) values of the fitting results are shown in Table 3.

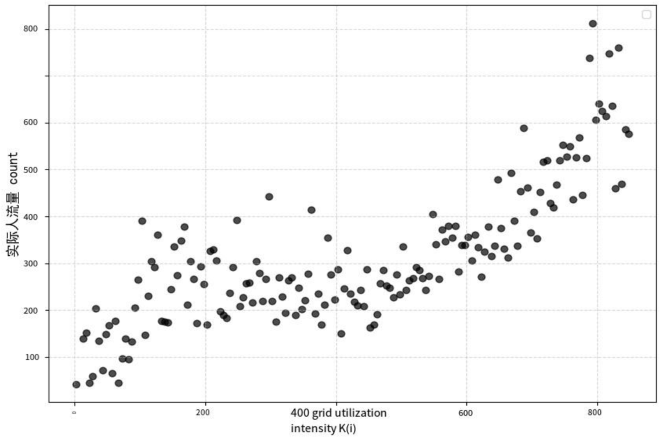

Figure 22. Scatter distribution diagram of grid utilization intensity vs. actual traffic.

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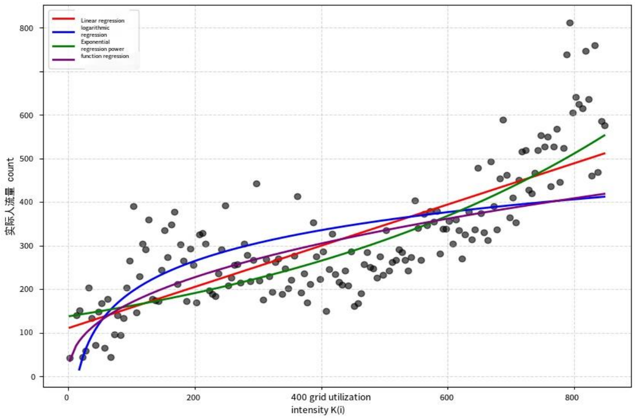

Figure 23. Grid utilization intensity vs. actual flow model fitting diagram.

Table 3. Regression model fitting effect table.

Model	Relationship	R^2	RMSE	MAE	MAPE
Linear regression model	$y = 0.473x + 110.533$	0.615	91.35	72.61	28.57%
Exponential regression model	$\mathbf{y = 137.578 \times e^{0.0016x}}$	**0.676**	**83.83**	**64.02**	**26.00%**
Power regression model	$y = 24.162 \times x^{0.423}$	0.509	103.17	77.74	27.89%
Logarithmic regression model	$y = 102.192 \times \ln(x) - 276.808$	0.432	110.91	87.82	35.29%

The correlation coefficient between the linear regression model (R^2 =0.615) and the exponential regression model (R^2 =0.676) was large, indicating that grid utilization intensity could explain most of the actual traffic variation. The statistical correlation between the two models was significant, and the traffic showed an upward trend with the increase in grid utilization intensity. In addition, the index regression model performed better in RMSE, MAE, and MAPE, but the metric values were smaller on average, whereas the exponential regression model showed fitting error fluctuation and lightness, but fitting accuracy was higher, as shown in Figure 24; thus, in this study, the actual flow values are calculated using the index regression model.

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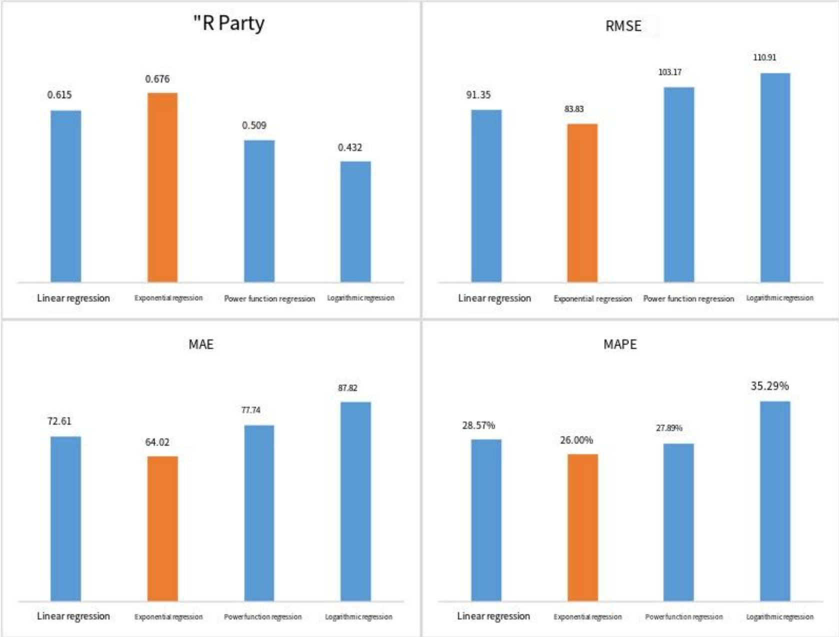

Figure 24. Model correlation coefficient and error comparison chart.

5. Conclusions

To effectively alleviate the hidden danger of oversaturated spatial flow in super high-rise buildings, transportation hubs and other facilities by optimizing the design scheme at the source, this paper conducts an in-depth study on the problem of spatial flow estimation in the architectural design stage. Firstly, based on the detailed data from pedestrian micro-simulation in buildings, the influencing factors of spatial flow are thoroughly analyzed from two aspects: spatial structure and pedestrian demand. Furthermore, by introducing the visibility integration degree of space syntax and the method for defining the OD influence range considering obstacle detouring proposed in this paper, a spatial utilization intensity index is designed, which comprehensively incorporates the above two factors. On this basis, regression analysis is employed to realize spatial flow estimation based on the spatial utilization intensity index. Finally, taking the basement 1 floor of the Shenzhen Bay Super Headquarters Base C Tower connected with the metro as a case study, the effectiveness of the proposed method is verified, with MAPE of 26%.

Due to the limitation of research data volume, the building spatial flow estimation using regression analysis in this paper does not accurately reflect the relationship between relevant influencing factors and spatial flow to a certain extent. In the future, with the continuous improvement of relevant research data and the enhancement of computing power, research on deep learning-based building spatial flow estimation methods can be considered. Meanwhile, this study only focuses on the flow of unit grids. In later stages, based on this research, larger-scale regional flow estimation and grade classification can be carried out to provide a better basis for architectural design.

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