RESEARCH ARTICLE

Tourist flow analysis and regulation strategy in tourist attractions based on spatiotemporal evolution and internet of things big data

Shan He*

Henan Institute of Economics and Trade, Zhengzhou, Henan, China.

Received: August 19, 2024; **accepted:** December 12, 2024.

In the information wave of the 21st century, human society has ushered in unprecedented technological innovation, especially the application of the Internet of Things (IoT) and big data technology, which is bringing profound changes to many fields. However, in the tourism industry, how to effectively use these emerging technologies to solve problems such as passenger flow control, tourist experience improvement, and resource utilization efficiency in scenic area management is still one of the key and difficult points of current scientific research. This study constructed a theoretical framework and methodology for passenger flow analysis and regulation strategies in tourist attractions based on spatiotemporal evolution and IoT big data. The spatiotemporal evolution model was defined, and the spatiotemporal trend of passenger flow was demonstrated through the diffusion equation and the description of external factors. The data collection design considered a variety of technical means such as video surveillance and image recognition, radio frequency identification (RFID), sensor networks, and mobile device positioning. Data processing and analysis methods included data preprocessing, spatiotemporal series analysis, and multivariate linear regression models to reveal the spatiotemporal distribution of passenger flow and its influencing factors. Through empirical evaluation, the results showed that dynamic fare adjustment and tourist diversion strategies could effectively balance passenger flow distribution, improve tourist satisfaction, and improve environmental and resource utilization efficiency. This study provided a scientific basis for the regulation and management of tourist flow in scenic spots and a reference for similar studies in the future.

Keywords: spatiotemporal evolution; Internet of Things; big data; tourist attraction passenger flow analysis; regulation strategy.

***Corresponding author:** Shan He, Henan Institute of Economics and Trade, Zhengzhou 450000, Henan, China. Email: heshan188@hotmail.com.

Introduction

In the information wave of the 21st century, human society has ushered in unprecedented technological innovation. The rapid development of information technology has not only profoundly changed human's daily lives, but also given wings to the transformation and upgrading of various industries. In particular, the Internet of Things (IoT) and big data technology are leading a quiet revolution, bringing disruptive changes to many fields. In this technological torrent, the tourism as an ancient and vibrant industry is no exception and is undergoing an important transformation period from traditional to intelligent. In this context, the modernization process of tourist scenic area management has been given new missions and challenges and has also gained unprecedented development opportunities [1]. As an intelligent information network system integrating perception, transmission, and processing, the core technology of IoT is “Internet of Everything”. In the tourist scenic area scenario, by deploying various sensors, intelligent monitoring equipment, radio frequency identification (RFID) tags, and other IoT components at key locations, a large amount of multi-dimensional data on tourist behavior, environmental conditions, facility usage, *etc*. can be monitored and collected in real time. These data cover many aspects from tourist entry flow, route preferences, stay time to congestion in specific areas, providing managers with unprecedented insights [2]. Big data technology uses advanced algorithms and computing architectures to clean, integrate, and analyze these data, revealing the spatiotemporal patterns and peak-valley patterns of tourist flows, and predicting the trend of passenger flow in the future. This process not only overcomes the limitations of traditional statistical methods in data processing scale and complexity, but also provides solid data support for scientific decision-making [3].

Combining spatiotemporal analysis methods with IoT big data, tourist attraction management has entered a new stage of refined operation. Through the comprehensive analysis of historical data and real-time information, scenic area managers can predict the flow pressure during peak hours in advance and take measures such as dynamically adjusting ticket sales, optimizing tour routes, and implementing time-sharing reservations to effectively alleviate congestion and improve tourist satisfaction. On the other hand, long-term passenger flow data analysis helps to identify the threshold of scenic area carrying capacity, guide the rational allocation of resources and the formulation of protection measures, and ensure the sustainable use of natural resources and cultural heritage. In addition, big data technology can also promote personalized service innovation, push customized information and services by analyzing tourist preferences, and enhance the interactivity and personalization of tourism experience [4]. To fully understand how environmental factors influence tourism decisions, it is necessary to consider them from a more diverse perspective. Environmental factors including natural landscapes, climate conditions, air quality, water quality, and noise pollution significantly affect tourists' experiences, impact environmental factors on tourism choices and corresponding management strategies [5, 6]. Scenic area managers can adopt a series of management strategies to cope with the impact of environmental factors on tourism choices, which include the enhancement of the quality of natural landscape through plant greening and landscape restoration to attract tourists; optimization of climatic conditions by using shading facilities and spray cooling to improve the comfort of tourists; improvement of air quality by implementing air pollution control measures; ensuring the cleanliness of the water body by adopting water purification technology; and reduction of noise pollution by soundproofing facilities and restricting noise sources to reduce noise pollution. These measures not only help to enhance the tourist experience of visitors but also are of great significance to the sustainable development of the scenic area [7, 8].

However, considering the difficulty and cost of data collection, the specificity of different scenic spots, and the complexity of technical implementation, the current studies in this field have certain limitations such as the representativeness of sample selection and the general applicability of the model, which need to be further explored. This study committed to explore the analysis and regulation strategy of tourist scenic spot passenger flow based on spatiotemporal evolution and IoT big data to provide a novel and practical system for scenic spot management by using spatiotemporal analysis technology of geographic information system (GIS), data acquisition capability of IoT, and big data analysis methods. This study focused on developing and optimizing dynamic models suitable for scenic spot passenger flow prediction including hybrid models combining autoregressive integrated moving average (ARIMA) and long short-term memory (LSTM) to improve prediction accuracy [9, 10]. Through accurate passenger flow analysis and regulation, it could effectively improve the travel experience of tourists and promote the high-quality development of tourism under the premise of protecting the natural environment and cultural heritage and open a new chapter of smart tourism. The multidimensional interdisciplinary research framework proposed in this study not only provided a powerful tool for solving the current problems, but also was a key driving force for promoting the development of tourism towards intelligence and sustainability [11].

Materials and methods

Spatiotemporal evolution model construction

A spatiotemporal evolution model was constructed as the core of the study to capture and predict the trend of tourist flow with time and space. Modelling usually started with defining basic variables. The passenger flow at a two-dimensional spatial location (x, y) and time t was expressed as Q (x, y, t), where (x, y) were spatial coordinates and t was a time variable. The space-time evolution process could be abstracted into the equation (1), and the specific model flow chart was shown in Figure 1.

$$\frac{\partial Q}{\partial t} = D\nabla^2 Q + S(Q, x, y, t) \quad (1)$$

The data of the model came from many sources. The application of IoT in data acquisition system included various sensors and intelligent devices. Taking scenic spots as an example, data acquisition design should consider the following aspects including video surveillance and image recognition using high-definition cameras combined with image recognition technology to identify and count tourists; RFID and sensor network to deploy RFID tags and environmental sensors such as temperature and humidity, noise sensors, collect environmental data E(t), and visitor density D(x, y, t) in specific areas; and mobile device positioning to track the travel path of tourists through GPS data of tourists 'mobile phones to form a position sequence [12, 13].

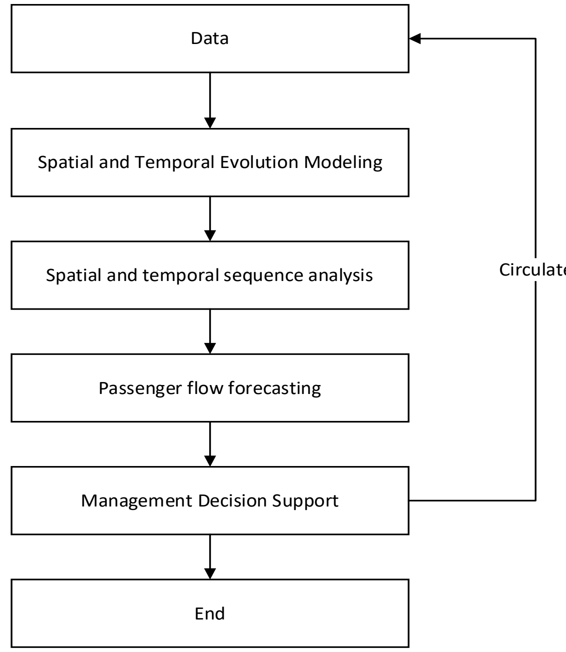

Figure 1. Model flow chart.

Data processing and analysis

Data preprocessing included cleaning, format conversion, missing value processing, and outlier detection. The relationship between estimation and observation and the difference between the two time points was shown in equation 2, which showed that the estimation was a weighted average of the observed values based on the proportion of time between two points.

$$Q_{est}(t_i) = Q_{obs}(t_{i-1}) + \frac{t_i - t_{i-1}}{t_{i+1} - t_{i-1}}(Q_{obs}(t_{i+1}) - Q_{obs}(t_{i-1})) \quad (2)$$

where $Q_{est}(t_i)$ was an estimate of the time and was calculated from observations and historical data. $Q_{obs}(t_{i-1})$ was the observation at time provided direct information about the state of the system. $\frac{t_i - t_{i-1}}{t_{i+1} - t_{i-1}}$ was a weighting factor that reflected the proportion of time between two points and was used to adjust for the influence of neighboring observations. $Q_{obs}(t_{i+1})$ was the observed value of a moment, which, although not directly used in this formula, might be a prediction or estimate of the next moment. Time series analysis focused on the variation of data with time, while spatial statistics focused on spatial distribution characteristics and their dependencies. The combination of the two could reveal the dynamic behavior of complex systems more comprehensively as follows [14].

$$Q_t = c + \phi_1 Q_{t-1} + \ldots + \phi_p Q_{t-p} - \theta_1 \varepsilon_{t-1} - \ldots - \theta_q \varepsilon_{t-q} \quad (3)$$

where *c* was the constant term. The model parameters, *p* and *q*, were the orders of the autoregressive and moving average terms, respectively. *q* was the error term. Spatiotemporal series analysis is a comprehensive method combining time series analysis and spatial statistics, which is effective in dealing with data with spatiotemporal dimensions, especially in exploring the spatiotemporal distribution law of tourist flow in scenic spots and predicting future trends. Time series analysis focused on the variation of data with time, while spatial statistics focused on spatial distribution characteristics and their dependencies. The combination of the two could reveal the dynamic behavior of complex systems more comprehensively as below.

$$f_t = \sigma(W_f \cdot [h_{t-1}, x_t] + b_f), \quad i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i), \ldots \quad (4)$$

The equation 4 described the computation of a sequence function, which was a linear combination with activation functions and showed that the function value at each moment was calculated from the characteristics of the previous moment, the current moment, and the corresponding weights and bias terms. f_t was the function value at time t, which was the product of the input feature and the weight matrix through the activation function. W_f and W_i were weight matrices that determined how input features affected output. h_{t-1} and x_t were input characteristics including the state information of the previous time and the new information of the current time. b_f and b_i were bias terms that added a constant offset to the linear combination. σ was an activation function that converted linear combinations into nonlinear outputs [14].

Strategy formulation methodology

When formulating passenger flow control strategy based on data analysis, it was necessary to comprehensively consider the comprehensive influence of passenger flow characteristics, scenic area carrying capacity, and tourist experience. The strategy development process was meticulous, starting with problem identification and identifying key issues through in-depth data analysis such as identifying overcrowding in specific areas of the attraction. Goal setting then focused on quantifying the desired effect of regulation such as establishing a target percentage for reducing congestion at a particular peak hour, for example, a congestion reduction target of 20%. At the stage of strategy design, innovation and practicality were emphasized, and technology-enabled schemes were adopted including dynamic ticketing system, whose ticket price model, where and were strategic adjustment parameters, dynamically adjusted ticket prices according to predicted passenger flow to balance supply and demand. Meanwhile, tourist diversion strategy intelligently guided tourists to relatively loose tour routes through real-time analysis of tourist density distribution D(x, y, t), and dispersed passenger flow pressure [15, 16].

Analysis on the temporal and spatial distribution of passenger flow

GIS and time series analysis techniques were applied to reveal the distribution characteristics of tourist flow in time and space to explore visitor behavior patterns and their fluctuations over time. Through rigorous analysis, the methods would provide accurate guidance for management decisions. By using GIS technology, the spatial distribution pattern of tourists in scenic spots was first revealed through hot spot analysis. Kernel density estimation (KDE) is a commonly used tool that displays spatial distribution characteristics by estimating the density value of each point. The mathematical expression was shown in equation 5 [17, 18].

$$D(x, y) = \frac{1}{nh^2} \sum_{i=1}^{n} K\left(\frac{x - x_i}{h}, \frac{y - y_i}{h}\right) \quad (5)$$

This formula described a KDE procedure for estimating probability density functions and showed that the density estimate was obtained by multiplying the values at the sample points by the kernel function and integrating them over space. $D(x, y)$ were density estimates at two points, reflecting the probability density at that location. K was Kernel function that defined the similarity between sample points, usually a Gaussian kernel. n was the number of samples, *i.e.* the number of training data. h was bandwidth parameter, which controled the width of kernel function and affected the accuracy and smoothness of estimation. In this way, the high-density areas such as popular attractions and low-density areas within the scenic spot could be identified, providing a basis for resource allocation and route planning. Time series analysis was used to explore and predict trends, seasonality, and fluctuations in visitor traffic over time. The ARIMA model was a classic tool whose general form was shown as follows [19].

$$X_t = c + \phi_1 X_{t-1} + \cdots + \phi_p X_{t-p} + \theta_1 \epsilon_{t-1} + \cdots + \theta_q \epsilon_{t-q} + \epsilon_t \quad (6)$$

This linear regression model described how a sequence of independent variables affected the dependent variable, while the effects of random error terms were considered. By fitting ARIMA models, the seasonal fluctuations, long-term trends, and any possible cyclical changes in passenger traffic could be revealed and predicted, providing time-dimensional management guidance for scenic spot operations. To understand the spatiotemporal characteristics more comprehensively, spatiotemporal joint analysis was performed including spatiotemporal autocorrelation analysis to measure the correlation of passenger flow distribution in space and time by calculating spatiotemporal Moran's I index as follows [20].

$$I_s = \frac{n}{\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}} \frac{\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}(X_i - \bar{X})(X_j - \bar{X})}{\sigma^2} \quad (7)$$

where I_s appeared to be some form of covariance or square of the correlation coefficient, which might be a weight matrix used to calculate the difference between two sample sets. This formula described the strength of the statistical relationship between two sample sets.

Discussion on influencing factors

It was particularly important to identify and quantify the key influencing factors in the process of understanding the internal mechanism of tourist flow fluctuation in tourist attractions. This study provided data-driven decision support for scenic spot management by constructing fine multiple linear regression models to deeply analyze the detailed effects of holiday effects, weather changes, and special events on passenger flow [21, 22]. The core model used a multiple linear regression framework that effectively captured complex relationships between multiple independent variables (influencing factors) and dependent variables (passenger traffic). The model was expressed as below.

$$Q_t = \beta_0 + \beta_1 H_t + \beta_2 T_t + \beta_3 R_t + \beta_4 E_t + \epsilon_t \quad (8)$$

The equation included the predicted passenger flow, the coefficient corresponding to the influencing factors, the holiday status (H_t) (1 for holidays and 0 for non-holidays), temperature (T_t), precipitation (R_t), special events (E_t) (1 for activities and 0 for none), and the model error term, reflecting random fluctuation. Based on the analysis of influencing factors, the specific impact of different factors on the flow of tourists in scenic spots could be clearly quantified and provide quantitative basis for the strategic planning of scenic spot managers. Through the analysis of these factors, scenic spot managers could allocate resources and prepare for emergencies more effectively [23, 24].

Implementation strategy

Based on the deep analysis and understanding of the temporal and spatial characteristics of tourist flow and its influencing factors, a series of intelligent regulation strategies were designed and proposed. The fundamental purpose of the regulation strategy was to create a tourism environment that could satisfy the high-quality tourist experience, effectively protect the natural and cultural heritage, and optimize the management efficiency of the scenic spot. The core objective of the regulatory strategy was to construct a tourism environment that ensured visitors enjoy a high-quality tourism experience and optimized the management effectiveness of scenic spots while protecting natural resources and cultural heritage, which specifically covered three key objectives of balancing the visitor experience with the carrying capacity of the scenic spot to control the visitor flow, ensure the carrying capacity, prevent overcrowding, and thus enhance the comfort of the tour; emphasizing resource and environmental protection to mitigate the adverse impact on natural and cultural resources and maintain the ecosystem balance; pursuing management efficiency with the help of intelligent means to improve operational efficiency, reduce cost consumption, accelerate response speed, enhance flexibility, and improve management efficiency in an all-round way. To achieve these goals, this study planed a set of intelligent control strategy combination as implementing dynamic ticket reservation system by flexibly adjusting the number of tickets issued according to the passenger flow prediction model, pre-regulating the inflow of tourists, effectively alleviating the congestion and queuing phenomenon on the spot; implementing the tourist diversion strategy utilizing real-time passenger flow data analysis and GIS technology, guiding tourists to relatively empty areas through mobile phone application programs and on-site indicators, and balancing the distribution of tourists; developing an intelligent early warning system to integrate real-time monitoring and analysis platform to predict and warn crowd density and potential safety hazards to ensure rapid response and intervention. These intelligent control measures worked together to enhance the visitor experience, protect environmental resources, and optimize management efficiency. To ensure the effective implementation and efficient implementation of intelligent regulation strategies, this research planed a detailed implementation framework, covering three dimensions of technical path, resource allocation, and policy support to systematically promote the intelligent transformation of tourist attractions (Figure 2). The technology implementation path focused on building robust digital infrastructure by enhancing network coverage of attractions and deploying IoT devices such as RFID tags, smart cameras, and various sensors to ensure immediate data collection. A cloud computing platform was built to integrate high-performance server clusters, process massive data, support big data analysis and model prediction, and realize real-time response of dynamic management. Meanwhile, intelligent applications for tourists and management personnel were developed to integrate reservation service, navigation and early warning functions, and improve interactive convenience and management efficiency. The policy supporting system focused on system construction, formulation and implementation of reservation system, flow management rules, and environmental protection standards, and clarification of rights and responsibilities and incentives and constraints. Through publicity and education with the help of media and social platforms, tourists were guided to make reservations to visit culture and promoted civilized travel fashion. Establishment of an effect evaluation mechanism and providing regular feedback would ensure that the strategies and technologies were flexibly optimized according to actual conditions and continuously optimized and upgraded.

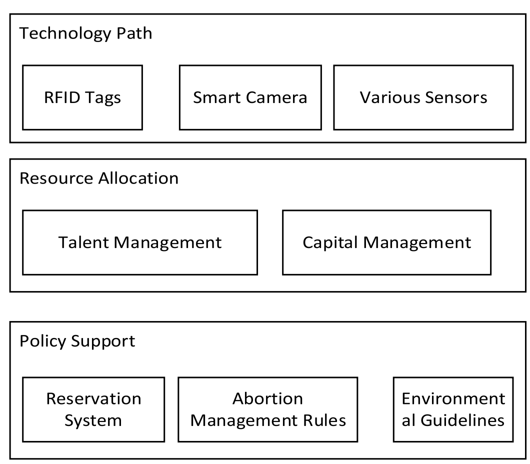

Figure 2. Implementation framework.

Experimental design

The official tourism industry data provided by the National Tourism Administration Data Center were employed in this study, which covered tourism activity records from January 1, 2023 to December 31, 2023 with a total of 100,000 records. By retrieving and segmenting these data, 80,000 records (80%) was used for model training and 20,000 records (20%) was used for model testing. The data types included time series data as the number of tourists, holidays, weather, and special events; financial data as total revenue and ticket sales; tourist feedback data as satisfaction surveys and social media sentiment analysis; and environmental monitoring data as garbage volume and water resource consumption. These data were used together to analyze tourist flow characteristics, evaluate economic impacts, understand tourist experiences, and evaluate the impact of smart management strategies on scenic area environments. The representative tourist attractions were selected as research objects to ensure that the dataset contained sufficient space-time span and typical influencing factors including different seasons, holidays, typical weather conditions, and special events. Data sources included, but were not limited to, historical foot traffic records, weather databases, activity logs, social media data, visitor survey feedback, *etc*. To ensure the reliability of the analysis, all data underwent strict quality inspection and pretreatment such as outlier elimination, missing value filling, *etc*. The evaluation of the effect before and after the implementation of the strategy was an important link to verify the effectiveness of the regulation strategy. Specific operations included the comparison between control group (unimplemented strategy area) and experimental group (implemented strategy area); multi-dimensional evaluation that not only paid attention to passenger flow indicators like congestion improvement and tourist distribution balance, but also examined multi-dimensions such as tourist satisfaction, merchant income, environmental impact, resource utilization efficiency, *etc*. A particular scenic spot was selected to analyze the changes of passenger flow and revenue after implementing the dynamic fare adjustment strategy on holidays

Results and discussion

Comparative analysis of passenger flow

During the study period, an intelligent management strategy was adopted by implementing a dynamic ticket booking system and adjusting ticket issuance using a predictive model to control tourist flow to effectively alleviate on-site congestion and reduce waiting time in queues. In addition, an intelligent early warning system was constructed to integrate a real-time monitoring and analysis platform to warn of crowd density and potential safety risks, ensuring rapid response and intervention, thereby improving the overall tourist experience, protecting natural resources, and optimizing scenic spot management efficiency. The results showed that, during the peak holiday period, the control group had a passenger flow of 5,000 people, while the experimental group had a passenger flow of 6,000 people before the adjustment and dropped to 5,000 people after the adjustment. During the holiday trough period, the control group showed a passenger flow of 2,000 people, while the experimental group had a passenger flow of 1,800 people before the adjustment and increased to 2,500 people after the adjustment. During non-holiday working days, the control group demonstrated a passenger flow of 3,000 people, while the experimental group showed a passenger flow of 3,200 people before the adjustment and then 3,100 people after the adjustment. The results demonstrated a reduction of passenger flow during the peak period, while the passenger flow during the trough period increased. However, the passenger flow on non-holiday working days also showed a decrease trend, which suggested the effectiveness of the experimental group's strategy in balancing the distribution of passenger flow. By comparing the data before and after adjustment, the results indicated that the passenger flow decreased significantly in peak hours, increased in trough hours, and the total revenue was stable or increased.

Comparative analysis of income changes

In terms of income changes, the total income of the control group in January was 120 million Chinese yuan (¥), while the total income of the experimental group was ¥150 million before adjustment and ¥145 million after adjustment. After the implementation of dynamic ticket price adjustment within one month, the total income decreased slightly, which might reflect the impact of ticket price reduction on income. However, the slight decrease in total income might be compensated by the increase in the number of tourists, especially during low seasons and weekdays. However, if the numbers of tourists and the total revenue dropped sharply, it was necessary to analyze whether the strategy excessively suppressed demand and adjust the strategy parameters.

Tourist satisfaction survey

The questionnaire survey results showed that, after the adjustment, the average scores of ticket rationality, travel experience, service attitude, and overall satisfaction all increased. Ticket rationality increased from 3.5/5.0 before adjustment to 4.0/5.0, while travel experience increased from 4.2/5.0 to 4.5/5.0 and service attitude increased from 4.0/5.0 to 4.1/5.0 with the overall satisfaction increased from 3.9/5.0 to 4.2/5.0. The results indicated that the strategy of the experimental group had achieved positive results in improving tourist satisfaction.

Evaluation of environmental and resource utilization efficiency

The evaluation of environmental and resource utilization efficiency showed that the experimental group demonstrated a significant impact on environmental and resource efficiency with the daily garbage output being dropped from 1.2 tons to 1.0 tons, the daily water consumption being dropped from 300 m^3 to 270 m^3, and the traffic congestion index being dropped from 4.5/10 to 3.2/10. These improvements showed that the experimental group strategy was effective in improving resource utilization efficiency and reducing environmental pollution.

Analysis of tourist stay time

The results showed that, during the peak holiday period, the average stay time of the control group was 3.5 hours, while the experimental group was 4 hours before adjustment and 4.5 hours after adjustment. During the holiday trough period, the average stay time of the control group was 2 hours, while the experimental group was 2.5 hours before adjustment and 3 hours after adjustment. During non-holiday working days, the average stay time of the control group was 2 hours, and the experimental group was 2.5 hours before and 3 hours after adjustment. The experimental group provided tourists with more consumption opportunities and improved the quality of their experience by increasing the length of time they stayed in the scenic area, especially during peak holiday periods.

Social media influence analysis

The social media influence analysis showed that the experimental group strategy had a positive impact on social media interactions. The number of positive mentions increased from 10,000 to 15,000, while the number of negative mentions decreased from 200 to 150. The topic heat index increased from 700 to 900, and the interaction rate increased from 5% to 8%. These improvements further quantified the effectiveness of the strategy.

References

1. Cheng G, He CL. 2022. Analysis of bus travel characteristics and predictions of elderly passenger flow based on smart card data. Electron Res Arch. 30(12):4256-4276.
2. Fan Y, Zhang F, Jiang S, Gao C, Du Z, Wang Z, *et al*. 2020. Dynamic robustness analysis for subway network with spatiotemporal characteristic of passenger flow. IEEE Access. 8:45544-45555.
3. Yuan F, Sun H, Kang L, Wu J. 2020. Passenger flow control strategies for urban rail transit networks. Appl Math Model. 82:168-188.
4. Liang J, Lyu G, Teo C, Gao Z. 2023. Online passenger flow control in metro lines. Operations Research. 712(2):768-775.

5. Li W, Guan H, Han Y, Zhu H, Wang A. 2022. Short-term holiday travel demand prediction for urban tour transportation: A combined model based on STC-LSTM deep learning approach. Ksce J Civ Eng. 26(9):4086-4102.
6. Li D, Deng L, Cai Z. 2020. Statistical analysis of tourist flow in tourist spots based on big data platform and DA-HKRVM algorithms. Pers Ubiquit Comput. 24(1):87-101.
7. Xu Z, Zhu X, Wei G, Ouyang X. 2021. Spatio-temporal evolution and mechanism analysis of China's regional innovation efficiency. Sustainability-Basel. 13(19):11089.
8. Tan Q, Ling X, Chen M, Lu H, Wang P, Liu W. 2019. Statistical analysis and prediction of regional bus passenger flows. Int J Mod Phys B. 33(11):1950094.
9. Liang J, Zang G, Liu H, Zheng J, Gao Z. 2023. Reducing passenger waiting time in oversaturated metro lines with passenger flow control policy. Omega-Int J Manage S. 117:102845.
10. Zhang T, Yuan J, Chen YC, Jia W. 2021. Self-learning soft computing algorithms for prediction machines of estimating crowd density. Appl Soft Comput. 105:107240.
11. Yu S, Luo A, Wang X. 2023. Railway passenger flow forecasting by integrating passenger flow relationship and spatiotemporal similarity. Intell Autom Soft Co. 37(2):1877-1893.
12. Wang J, Kong X, Zhao W, Tolba A, Al-Makhadmeh Z, Xia F. 2018. STLoyal: A spatio-temporal loyalty-based model for subway passenger flow prediction. IEEE Access. 6:47461-47471.
13. Kong JJ, Zhang C. 2018. Critical subway stations identification for passenger flow control by applying network controllability. J Chin Inst Eng. 41(6):530-537.
14. Zhou Y, Chen J, Zhong M, Li Z, Zhou W, Zhou Z. 2023. Risk analysis of crowd gathering on metro platforms during large passenger flow. Tunn Undergr Sp Tech. 142:105421.
15. Li X, Chen P, Chen F, Wang Z. 2018. Passenger flow analysis of Beijing urban rail transit network using fractal approach. Mod Phys Lett B. 32(10):1850001.
16. Li L. 2020. A crowd density detection algorithm for tourist attractions based on monitoring video dynamic information analysis. Complexity. 2020:6635446.
17. Gao Z, Zhang J, Xu Z, Zhang X, Shi R, Wang J, *et al*. 2020. Method of predicting passenger flow in scenic areas considering multisource traffic data. Sensor Mater. 32(11):3907-3921.
18. Zheng Z, Wang H, Liu W, Peng L. 2023. Toward real-time congestion measurement of passenger flow on platform screen doors based on surveillance videos analysis. Physica A. 612:128474.
19. Hu Y, Li S, Wang Y, Zhang H, Wei Y, Yang L. 2023. Robust metro train scheduling integrated with skip-stop pattern and passenger flow control strategy under uncertain passenger demands. Comput Oper Res. 151:106116.
20. Yuan Y, Shao C, Cao Z, Chen W, Yin A, Yue H, *et al*. 2019. Urban rail transit passenger flow forecasting method based on the coupling of artificial fish swarm and improved particle swarm optimization algorithms. Sustainability-Basel. 11(24):7230.
21. Li X, Bai Y, Su K. 2021. Collaborative passenger flow control of urban rail transit network considering balanced distribution of passengers. Mod Phys Lett B. 35(30):2150461.
22. Li H, Wang Y, Xu X, Qin L, Zhang H. 2019. Short-term passenger flow prediction under passenger flow control using a dynamic radial basis function network. Appl Soft Comput. 83:105620.
23. He B, Liu K, Xue Z, Liu J, Yuan D, Yin J, *et al*. 2021. Spatial and temporal characteristics of urban tourism travel by taxi: A case study of Shenzhen. Isprs Int J Geo-Inf. 10(7):445.
24. He L, Chen L, Liu J, Roberts C, Yu S, Feng X. 2022. Passenger flow-oriented metro operation without timetables. Appl Sci-Basel. 12(10):4999.