Service Quality Evaluation of Civil Airports Based on CRITIC-Bidirectional Grey Possibility Clustering Model

ZU Lili, *LI Xun*, *WANG Junjie**, *DANG Yaoguo*

College of Economics and Management, Nanjing University of Aeronautics and Astronautics, Nanjing 211106, P. R. China

(Received 25 May 2025; revised 15 November 2025; accepted 10 December 2025)

Abstract: With the rapid development of the aviation industry, air travel has become one of the most important modes. Improving the service quality of civil aviation airports is crucial to their competitiveness. This study intends to develop a scientific and rational evaluation methodology and framework for assessing service quality in civil aviation airports, thereby providing a theoretical foundation and practical guidance for enhancing service standards in the aviation industry. First, the study constructs a CRITIC-bidirectional grey possibility clustering model, which uses the CRITIC method to determine the weights of indicators and integrates the forward grey possibility clustering model and the inverse grey possibility clustering model to determine possibility functions from two perspectives. Second, a service quality evaluation index system for civil airports is constructed from four dimensions, and the weights of each index within the system are subsequently calculated. Finally, the constructed model is applied to evaluate the service quality of nine domestic civil airports. Based on the clustering results, targeted countermeasures and suggestions are proposed. Empirical results demonstrate that, compared to the traditional grey possibility clustering model, the proposed model balances the objectivity of indicator weighting, the objectivity of possibility function construction, and the simplicity of the computational process, thereby possessing significant theoretical and practical implications.

Key words: CRITIC method; grey clustering; possibility functions; civil airport; service quality evaluation

CLC number: F562.8 **Document code:** A **Article ID:** 1005-1120(2026)01-0110-17

0 Introduction

Civil airports are pivotal contributors to economic development[1]. The service quality of these airports serves not only a crucial indicator of their operational performance but also a key factor in enhancing the overall passenger travel experiences. By conducting a scientific evaluation of service quality, airports can identify shortcomings, optimize resource allocation, and improve service processes. Thereby enhancing customer satisfaction, boosting the airport's competitiveness, and promoting its sustainable development[2].

To enhance the efficiency of service quality evaluation at civil airports, scholars have conducted extensive research on the indicator systems for such evaluations. Bai et al.[3] developed a comprehensive service quality evaluation system for civil airports, comprising 24 indicators across six dimensions, tangibility, reliability, assurance, empathy, responsiveness, and remediation, thereby ensuring the completeness of the evaluation framework. Zhu et al.[4] established an airport competitiveness evaluation system comprising ten indicators across four dimensions, airport infrastructure development, operational scale, service quality, and transportation-geographical conditions. Hu et al.[5] developed an airport operational efficiency evaluation system comprising 11 indicators across four dimensions: Stand operation efficiency, passenger boarding efficiency, aircraft taxiing efficiency, and collaborative efficiency. Li et al.[6] selected 23 influencing factors of airport service quality based on five di-

*Corresponding author, E-mail address: wangjj@nuaa.edu.cn.

How to cite this article: ZU Lili, LI Xun, WANG Junjie, et al. Service quality evaluation of civil airports based on CRITIC-bidirectional grey possibility clustering model[J]. Transactions of Nanjing University of Aeronautics and Astronautics, 2026,43(1):110-126.

http://dx.doi.org/10.16356/j.1005-1120.2026.01.009

mensions, airport ground transportation systems, airport environment, security screening, check-in services, and passenger services. Liao et al.[7] selected two key indicators, mandatory processes, and facilities & environment, as latent variables for airport service quality, based on the factor loadings of 35 airport service quality evaluation indicators and the significance of each quality dimension's impact on air travel behavioral intentions. Chu et al.[8] developed a passenger travel experience model for regional hub airports by comprehensively considering two dimensions, passenger satisfaction and delight. Ren et al.[9] constructed an airport service quality evaluation system comprising five secondary indicators, tangibility, responsiveness, empathy, security, and reliability, along with 19 influencing factors, using a three-tier dimensional framework, service environment quality, interaction process quality, and output outcome quality as the entry point. Wang et al.[10] selected 27 airport service quality evaluation indicators across three dimensions, physical, operational, and human factors. Pamucar et al.[11] selected nine primary indicators, including ground transportation and security screening, along with 49 sub-indicators based on the Skytrax rating system to evaluate airport efficiency. Jia et al.[12] selected 28 sub-indicators across four dimensions, social responsibility, economic feasibility, operational efficiency, and environmental friendliness. Grynia et al.[13] selected five indicators to conduct a quantitative evaluation of airport efficiency. Wang et al.[14] adopted operational and financial dimensions as indicators for airport performance evaluation. Kuo et al.[15] selected seven indicators, including time cost, convenience, and comfort, to construct an airport service quality evaluation system.

Numerous scholars have conducted research on the evaluation indicators of airport service quality. However, as shown in Table 1, some studies excessively pursue the comprehensiveness of evaluation results. Despite selecting a large number of indicators, several of them are highly correlated and exhibit significant information overlap, which undermines the validity of the assessment outcomes. Furthermore, while some studies have focused on critical factors such as time and efficiency, they have overlooked essential indicators like flight safety and passenger services. Additionally, some studies have adopted overly narrow indicators that fail to comprehensively capture the key dimensions of airport service quality evaluation.

Table 1 Studies on airport service quality evaluation indicators

Content	Literature	Summary
Research on evaluation indicators for airport service quality	Refs.[3, 6, 9-10]	The selected indicators are quite comprehensive; however, multiple indicators are highly correlated and exhibit significant information overlap, which undermines the validity of the evaluation results.
	Refs.[4-5, 12]	Although attention has been paid to key factors such as time and efficiency, critical indicators like flight safety and passenger service have been overlooked.
	Refs.[7-8, 11, 13-15]	The selection of indicators is too one-sided and fails to comprehensively cover the key dimensions of airport service quality evaluation.

Regarding the evaluation of service quality at civil airports, many scholars have employed clustering models for analysis. Zhang et al.[16] employed a systematic clustering analysis method to classify the service quality competitiveness of 39 major airports. Yang et al.[17] applied K-means clustering analysis to categorize the operational support service capabilities of 182 small and medium-sized airports across the country. Wang et al.[18] employed a grey possibility clustering model to evaluate the service level of the curb lane at airport terminals. Pauwels et al.[19] employed latent profile analysis to categorize regional airports in Western Europe into four distinct groups. Gao[20] conducted a cluster analysis of passenger traffic at U. S. airports using the K-shape clustering method. Urban et al.[21] employed a multi-dimensional two-step clustering analysis method to classify 42 airlines into seven distinct business models. Wen et al.[22] utilized a multiple correspondence clustering method to conduct a cluster evaluation of airline service quality and competitive positioning.

Currently, the applications of the grey possibility clustering (GPC) model in evaluating service quality at civil airports are relatively limited. GPC is a method that utilizes possibility functions to assign objects into predefined classes. Compared to other clustering methods, (1) GPC allows for the pre-definition of both the number of classes and their quality (e.g., superior or inferior); (2) it imposes no requirements on the size of the dataset, suitable for small samples; (3) it clusters objects based on possibility functions rather than relying on the calculation of Euclidean distances between data points. The GPC model has been applied to various fields, including quality risk assessment[23], bank efficiency evaluation[24], drought risk assessment[25], and innovation capability research[26]. However, in most of the aforementioned applications, the weights of clustering indicators are assigned directly by decision-makers, which can easily introduce human bias and result in a lack of scientific justification and persuasiveness in weight allocation. In contrast, objective weighting methods derive weights directly from the data themselves, ensuring impartiality and objectivity, thereby leading to more authentic and reliable evaluation results. Compared to other objective weighting methods, the CRITIC method[27] takes into account both the contrast intensity of the indicator data and the conflict between indicators. This comprehensive approach enables a more thorough and in-depth exploration of the intrinsic information within the data, avoiding double-counting highly correlated and redundant indicators. As a result, it yields more scientific and robust weighting outcomes.

Based on the research perspective, the GPC model can be categorized into forward GPC and inverse GPC. In the traditional forward GPC model, after defining the objects, indicators, and classes, objects are assigned to corresponding grey classes through the construction of possibility functions. However, the possibility function is primarily determined by the decision-maker's subjective preferences. Different decision-makers may construct different possibility functions, leading to inconsistent or even contradictory clustering results. This implies that the clustering outcomes are inherently subjective. Inverse GPC[28] is a method that quantitatively derives the possibility function based on partially known clustering results. This approach ensures that the final clustering outcomes remain consistent with the known partial results, thereby enhancing the objectivity of the clustering process. However, the inverse grey possibility clustering model involves complex computations. Moreover, in practical applications, partially known clustering results may not always be available, which limits the applicability of this method.

In summary, the following difficulties exist in objectively evaluating the service quality of civil aviation airports using the GPC model: (1) The possibility function of the forward GPC model is challenging to construct and often relies on subjective input from decision-makers, leading to significant uncertainty in the clustering results. (2) Although the inverse GPC model can quantitatively determine the possibility function, it may lack partially known clustering results to serve as input data in practical applications. (3) Determining indicator weights is challenging.

Building upon the aforementioned issues, this paper comprehensively considers the objectivity of indicator weights, the objectivity of clustering results, and the simplicity of model computation. A CRITIC-bidirectional grey possibility clustering model is constructed by integrating the CRITIC method, the forward GPC model, and the inverse GPC model. This model achieves complementary advantages of multiple methods, thereby enhancing the objectivity and accuracy of the clustering results.

The remainder of this paper is organized as follows: Section 1 constructs the CRITIC-bidirectional grey possibility clustering model. Section 2 establishes the service quality evaluation indicator system for civil airports and calculates the indicator weights. Section 3 uses the proposed model to cluster the service quality of nine domestic civil airports. Section 4 concludes the study.

1 CRITIC-Bidirectional Grey Possibility Clustering Model

1.1 CRITIC method

CRITIC method is a multi-criteria decision analysis approach that assesses the significance of indicators in accordance with their correlations. It offers an objective reflection on the importance of each indicator, mitigating the influence of human factors. Thus, it is commonly used for evaluating and selecting solutions. The CRITIC method include the following three steps.

(1) Dimensionless processing

Since all the indicators selected in this study are benefit-oriented ones, the data are standardized by formula $z_{ic}=\dfrac{x_{ic}-\min\limits_i x_{ic}}{\max\limits_i x_{ic}-\min\limits_i x_{ic}}$, where x_{ic} represents the observed value of object i regarding the secondary indicator c and z_{ic} the standardized value of x_{ic}.

(2) Calculation of the information carrying capacity

The cth indicator of the volatility is

$$S_c=\sqrt{\frac{\sum\limits_{i=1}^{n}(z_{ic}-\overline{z}_c)^2}{m-1}}$$

where $\overline{z}_c$ represents the mean of the data for the cth indicator. The cth indicator of the conflict is

$$R_c=\sum_{j=1}^{n}(1-r_{jc})$$

where r_{jc} represents the Pearson correlation coefficient between the jth and cth indicators. The information carrying capacity is $I_c=S_c\times R_c$.

(3) Determine objective weights

The weight of the cth indicator is $\eta_c=\dfrac{I_c}{\sum\limits_{c=1}^{n}I_c}$.

1.2 Bidirectional grey possibility clustering model

Definition 1 (Bidirectional grey possibility clustering model) In the evaluation system, there are n objects, m indicators, and s grey classes. The observation value of indicator $j\,(j=1,2,\cdots,m)$ for the ith $(i=1,2,\cdots,n)$ object is x_{ij}. Therefore, the method of classifying the ith object into the kth $(k\in\{1,2,\cdots,s\})$ grey class is called the grey possibility clustering model. In the GPC model, the challenge of analyzing all possible $f_j^k(\bullet)$ with given observed values $\boldsymbol{X}$ and clustering results is called the inverse grey possibility clustering (IGPC) model. The bidirectional grey possibility clustering model then arises from the integration of the forward GPC and the inverse GPC models. This model entails constructing possibility functions for clustering analysis and, based on known clustering results, quantitatively solving for all feasible possibility functions.

Definition 2 (Center-point triangular possibility functions)[29-30] In the evaluation system, there are n objects, m indicators, and s grey classes. Then, the possibility function value of object i belonging to grey class k with respect to indicator j is denoted as $f_j^k(x_{ij})$, and the possibility function of n evaluation objects regarding indicator j belonging to grey class k is denoted as $f_j^k(\bullet)$. Let the possibility function $f_j^k(\bullet)$ of the ith object belonging to the grey class k with respect to indicator j be the center-point triangular possibility function, as shown in Fig.1. λ_j^{k-1} is the center point of kth class, which means the point λ_j^k most likely belongs to the kth class regarding the jth index, and $\lambda_j^k=\dfrac{\lambda_j^{k-1}+\lambda_j^{k+1}}{2}$. Then, the possibility function value of observation x_{ij} for indicator j belonging to grey class k is

$$f_j^k(x_{ij})=\begin{cases}0 & x_{ij}\notin[\lambda_j^{k-1},\lambda_j^{k+1}]\\ \dfrac{x_{ij}-\lambda_j^{k-1}}{\lambda_j^k-\lambda_j^{k-1}} & x_{ij}\in(\lambda_j^{k-1},\lambda_j^k]\\ \dfrac{\lambda_j^{k+1}-x_{ij}}{\lambda_j^{k+1}-\lambda_j^k} & x_{ij}\in(\lambda_j^k,\lambda_j^{k+1})\end{cases} \tag{1}$$

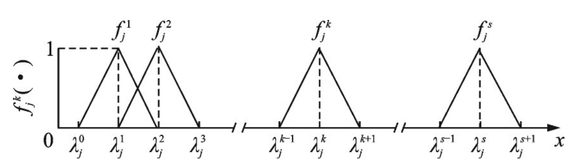

Fig.1 Center-point triangular possibility function

Definition 3 (Clustering coefficient matrix)[30] Assuming x_{ij} is the observed value of object i with respect to indicator j, $f_j^k(\bullet)$ is the center-point triangular possibility function, then

$$\sigma_i^k=\sum_{j=1}^{m} f_j^k(x_{ij})\eta_j \tag{2}$$

is called the clustering coefficient of object i belonging to grey class k, where η_j is the weight of indicator j.

The clustering coefficient vector of the object i is referred to as

$$\boldsymbol{\sigma}_i=(\sigma_i^1,\sigma_i^2,\cdots,\sigma_i^k,\cdots,\sigma_i^s) \tag{3}$$

The clustering coefficient matrix of n objects is referred to as

$$\boldsymbol{\sigma}=\begin{bmatrix}\sigma_1^1 & \sigma_1^2 & \cdots & \sigma_1^s\\ \sigma_2^1 & \sigma_2^2 & \cdots & \sigma_2^s\\ \vdots & \vdots & & \vdots\\ \sigma_n^1 & \sigma_n^2 & \cdots & \sigma_n^s\end{bmatrix} \tag{4}$$

If $\max\limits_{k=1}^{s}\{\sigma_i^k\}=\sigma_i^{k^*}$, it is considered that object i belongs to the grey class k^*.

Theorem 1 (Matrix representations of symmetric grey possibility functions)[28] In a GPC model, $f_j^k(\bullet)$ is the center-point triangular possibility function, which is composed of $2s$ line, as shown in Fig.2. The matrix of these lines is expressed as

$$\boldsymbol{Y}_j=\boldsymbol{M}_j x+\boldsymbol{N}_j \tag{5}$$

where $\boldsymbol{M}_j=\begin{bmatrix}(-1)^2/d_j\\(-1)^3/d_j\\ \vdots\\ (-1)^{2s+1}/d_j\end{bmatrix}$, $\boldsymbol{N}_j=\begin{bmatrix}[3d_j+(-1)^1(4\lambda_j^0+5d_j)]/4d_j\\ [3d_j+(-1)^2(4\lambda_j^0+9d_j)]/4d_j\\ \vdots\\ [3d_j+(-1)^{2s}(4\lambda_j^0+(4s+1)d_j)]/4d_j\end{bmatrix}$, $\boldsymbol{Y}_j=\begin{bmatrix}y_j^1\\y_j^2\\ \vdots\\ y_j^{2s}\end{bmatrix}$.

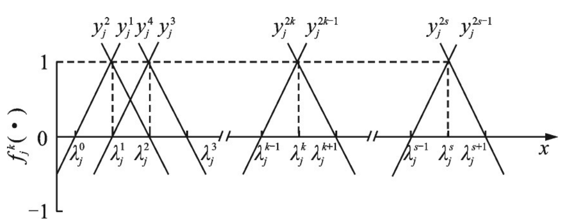

Fig.2 $2s$ lines of the symmetric center-point triangular possibility function

In Theorem 1, $f_j^k(\bullet)\in[0,1]$ is a piecewise function as defined in Eq.(1) and Fig.1. For each class, its center-point triangular possibility function consists of two-line segments. For example, for class k, the two-line segments of grey possibility function are $y_j^{2k}\in[0,1]$ and $y_j^{2k-1}\in[0,1]$ as portrayed in Fig.2. Then, $f_j^k(\bullet)$ has $2s$ line segments. The element y_j^l in $\boldsymbol{Y}_j$ represents the lth line. Therefore, for a given x_{ij}

$$f_j^k(x_{ij})=\begin{cases}y_j^{2k-1}(x_{ij}) & y_j^{2k-1}\in[0,1]\\ y_j^{2k}(x_{ij}) & y_j^{2k}\in[0,1]\\ 0 & y_j^{2k},y_j^{2k-1}\notin(0,1)\end{cases}$$

Definition 4 Let $\boldsymbol{e}_l$ be a $2s$-dimensional column vector where the lth entry is 1 and all other entries are 0. Let $\boldsymbol{J}_1$ and $\boldsymbol{J}_2$ be two 0-1 $s\times 2s$ matrices

$$\boldsymbol{J}_1=(\boldsymbol{e}_1,\ \boldsymbol{e}_3,\cdots,\ \boldsymbol{e}_{2k-1},\cdots,\ \boldsymbol{e}_{2s-3},\ \boldsymbol{e}_{2s-1})^{\mathrm{T}}$$
$$\boldsymbol{J}_2=(\boldsymbol{e}_2,\ \boldsymbol{e}_4,\cdots,\ \boldsymbol{e}_{2k},\cdots,\ \boldsymbol{e}_{2s-2},\ \boldsymbol{e}_{2s})^{\mathrm{T}}$$

As described in Theorem 1, $\boldsymbol{Y}_j$ is a $2s\times 1$ matrix. Then, let $\boldsymbol{Y}$ denote a $2s\times m$ matrix and $\boldsymbol{Y}=(\boldsymbol{Y}_1,\ \boldsymbol{Y}_2,\cdots,\ \boldsymbol{Y}_j,\cdots,\ \boldsymbol{Y}_m)$. Then, let $\boldsymbol{\Omega}_1$ and $\boldsymbol{\Omega}_2$ be two $s\times m$ matrices

$$\boldsymbol{\Omega}_1=\boldsymbol{J}_1\bullet\boldsymbol{Y},\ \boldsymbol{\Omega}_2=\boldsymbol{J}_2\bullet\boldsymbol{Y}$$

Definition 5 Assuming there are two $m\times n$ matrices $\boldsymbol{A}$ and $\boldsymbol{B}$, The Hadamard product is defined as $\boldsymbol{C}=\boldsymbol{A}\circ\boldsymbol{B}$ as the $m\times n$ matrix of the same order matrix $\boldsymbol{C}(p,q)=\boldsymbol{A}(p,q)\bullet\boldsymbol{B}(p,q)$. Define $\boldsymbol{\Omega}=\max\{\boldsymbol{\Omega}_1,\ \boldsymbol{\Omega}_2\}$ as the $m\times n$ matrix of the same order matrix $\boldsymbol{\Omega}(p,q)=\max\{\boldsymbol{\Omega}_1(p,q),\ \boldsymbol{\Omega}_2(p,q)\}$. According to Definition 4, it is known that both $\boldsymbol{\Omega}_1=\boldsymbol{J}_1\bullet\boldsymbol{Y}$ and $\boldsymbol{\Omega}_2=\boldsymbol{J}_2\bullet\boldsymbol{Y}$ are two $s\times m$ matrices. Let $\boldsymbol{\Delta}_1$ and $\boldsymbol{\Delta}_2$ be two $s\times m$ matrices, and $\boldsymbol{\Delta}_1(k,j)=|\boldsymbol{\Omega}_1(k,j)|$, $\boldsymbol{\Delta}_2(k,j)=|\boldsymbol{\Omega}_2(k,j)|$. Then, we can obtain the following $s\times m$ matrix $\boldsymbol{\Psi}$

$$\boldsymbol{\Psi}=\frac{\boldsymbol{\Omega}_1\circ\boldsymbol{\Omega}_2+\boldsymbol{\Delta}_1\circ\boldsymbol{\Delta}_2}{2\max\{\boldsymbol{\Omega}_1,\ \boldsymbol{\Omega}_2\}} \tag{6}$$

Theorem 2 (Matrix representations of grey clustering coefficient)[28] Assuming there are n objects, m indicators, and s grey classes in the evaluation system, x_{ij} is the observed value of object i with respect to indicator j. Given that the weight vector of m indicators is $\boldsymbol{\eta}=(\eta_1,\ \eta_2,\cdots,\eta_m)^{\mathrm{T}}$, and based on previous evaluation results, it is known that object i belongs to grey class k_i^*. $\boldsymbol{\Psi}$ is the matrix defined by Definition 5. Therefore, the matrix representations of grey clustering coefficient for object i can be represented as

$$\boldsymbol{\sigma}_i=(\sigma_i^1,\sigma_i^2,\cdots,\sigma_i^k,\cdots,\sigma_i^s)=\frac{\boldsymbol{\Omega}_{i1}\circ\boldsymbol{\Omega}_{i2}+\boldsymbol{\Delta}_{i1}\circ\boldsymbol{\Delta}_{i2}}{2\max\{\boldsymbol{\Omega}_{i1},\ \boldsymbol{\Omega}_{i2}\}}\bullet\boldsymbol{\eta}=\boldsymbol{\Psi}_i\bullet\boldsymbol{\eta} \tag{7}$$

Theorem 3 (IGPC model) Assuming there are n objects, m indicators, and s grey classes in the evaluation system, x_{ij} is the observed value of object i with respect to indicator j. Based on the previous evaluation results, it is known that object i belongs to grey class k_i^*, so $f_j^k(\bullet)$ should satisfy

$$\bigcap_{i=1}^{n} \max_{k=1}^{s}\left\{\sum_{j=1}^{m}(\boldsymbol{\Psi}_i(k,j)\times\eta_j)\right\}=\sigma_i^{k_i^*} \tag{8}$$

Eq.(8) is equivalent to inequation (9)

$$\bigcap_{i=1}^{n}\sum_{j=1}^{m}\left(\frac{\boldsymbol{\Omega}_{i1}(k_i^*,j)\times\boldsymbol{\Omega}_{i2}(k_i^*,j)+\boldsymbol{\Delta}_{i1}(k_i^*,j)\times\boldsymbol{\Delta}_{i2}(k_i^*,j)}{2\max\{\boldsymbol{\Omega}_{i1}(k_i^*,j),\boldsymbol{\Omega}_{i2}(k_i^*,j)\}}-\frac{\boldsymbol{\Omega}_{i1}(k,j)\times\boldsymbol{\Omega}_{i2}(k,j)+\boldsymbol{\Delta}_{i1}(k,j)\times\boldsymbol{\Delta}_{i2}(k,j)}{2\max\{\boldsymbol{\Omega}_{i1}(k,j),\boldsymbol{\Omega}_{i2}(k,j)\}}\times\eta_j\right)>0 \tag{9}$$

Proof When only one object i_1 is known to belong to class k^* under m indicators, inequation (10) can be obtained from Definition 3

$$\sigma_{i_1}^{k^*}\geqslant\sigma_{i_1}^{k}\qquad k\in s-\{k^*\} \tag{10}$$

According to Theorem 2, $\boldsymbol{\sigma}_{i_1}=(\sigma_{i_1}^1,\sigma_{i_1}^2,\cdots,\sigma_{i_1}^k,\cdots,\sigma_{i_1}^s)=\boldsymbol{\Psi}_{i_1}\bullet\boldsymbol{\eta}$, and $\sum_{j=1}^{m}(\boldsymbol{\Psi}_{i_1}(k,j)\times\eta_j)=\sigma_{i_1}^k$.

Therefore, inequation (10) can be transformed into

$$\sum_{j=1}^{m}(\boldsymbol{\Psi}_{i_1}(k^*,j)\times\eta_j)-\sum_{j=1}^{m}(\boldsymbol{\Psi}_{i_1}(k,j)\times\eta_j)>0 \tag{11}$$

According to Definition 5, $\boldsymbol{\Psi}_{i_1}(k,j)=\dfrac{\boldsymbol{\Omega}_{i_1 1}(k,j)\times\boldsymbol{\Omega}_{i_1 2}(k,j)+\boldsymbol{\Delta}_{i_1 1}(k,j)\times\boldsymbol{\Delta}_{i_1 2}(k,j)}{2\max\{\boldsymbol{\Omega}_{i_1 1}(k,j),\boldsymbol{\Omega}_{i_1 2}(k,j)\}}$.

Then inequation (11) is equivalent to inequation (12)

$$\sum_{j=1}^{m}\left[\frac{\boldsymbol{\Omega}_1(k_{i_1}^*,j)\bullet\boldsymbol{\Omega}_2(k_{i_1}^*,j)+\boldsymbol{\Delta}_1(k_{i_1}^*,j)\bullet\boldsymbol{\Delta}_2(k_{i_1}^*,j)}{2\max\{\boldsymbol{\Omega}_1(k_{i_1}^*,j),\boldsymbol{\Omega}_2(k_{i_1}^*,j)\}}-\frac{\boldsymbol{\Omega}_1(k,j)\bullet\boldsymbol{\Omega}_2(k,j)+\boldsymbol{\Delta}_1(k,j)\bullet\boldsymbol{\Delta}_2(k,j)}{2\max\{\boldsymbol{\Omega}_1(k,j),\boldsymbol{\Omega}_2(k,j)\}}\right]\bullet\eta_j>0 \tag{12}$$

where $k\in s-\{k^*\}$.

When the number of objects with known clustering results is n, the evaluation result of object i is only related to the possibility function $f_j^k(\bullet)$ of indicator j with respect to grey class k, and is independent of the observed values of other objects. Therefore, according to Eqs.(6, 12), for any object i

$$\bigcap_{i=1}^{n}\sum_{j=1}^{m}\left(\frac{\boldsymbol{\Omega}_1(k_i^*,j)\bullet\boldsymbol{\Omega}_2(k_i^*,j)+\boldsymbol{\Delta}_1(k_{i_1}^*,j)\bullet\boldsymbol{\Delta}_2(k_{i_1}^*,j)}{2\max\{\boldsymbol{\Omega}_1(k_i^*,j),\boldsymbol{\Omega}_2(k_i^*,j)\}}-\frac{\boldsymbol{\Omega}_1(k,j)\bullet\boldsymbol{\Omega}_2(k,j)+\boldsymbol{\Delta}_1(k,j)\bullet\boldsymbol{\Delta}_2(k,j)}{2\max\{\boldsymbol{\Omega}_1(k,j),\boldsymbol{\Omega}_2(k,j)\}}\times\eta_j\right)>0$$

Theorem 3 is proven.

1.3 Solving steps

The application of the CRITIC-bidirectional grey possibility clustering model proposed in this study includes four steps as follows.

Step 1 The initial step defines the input elements including the clustering indicators, objects, classes and raw data and then analyzes the partially known clustering results.

Step 2 The second step is to calculate the weight of each indicator using the CRITIC method based on the input.

Step 3 The bidirectional grey possibility clustering model is utilized to determine the required possibility functions. the IGPC model is established according to the inputs as given in Steps 1 and 2. And then the required inequalities are calculated by using the Theorems 1, 2 and 5.

Step 4 The last step calculates all available inequations, generates a set of available grey possibility functions, and obtains clustering coefficient matrix and clustering results.

2 Evaluation Indicator System for Civil Airport Service Quality

2.1 Construction of evaluation indicator system

The construction of an indicator system is the most fundamental step in evaluating the service quality of civil airports. Whether the indicator system is rationally constructed directly affects the evaluation results. Therefore, during the process of constructing the indicator system, it is essential to adhere to the principles of scientific rigor, systematicness, feasibility, relevance, differentiation, hierarchy, comparability, and data availability. According to Table 1, in constructing the service quality evaluation indicator system for civil airports, this study systematically reviews and integrated existing research (Refs.[3-15]) and focuses on the core principles of "multi-dimensional integration, refining and eliminating redundancy, and strengthening weaknesses to consolidate the foundation". First, it broadly incorporates widely recognized dimensions of service quality from existing studies, such as operational support, safety assurance, passenger care, and airport environment, laying a comprehensive framework for the system. Subsequently, targeted revisions are made to address two prominent issues commonly found in existing research, indicator information overlap and missing key dimensions. On one hand, by eliminating highly correlated and semantically redundant indicators, efforts are made to enhance the independence and representativeness of the indicator set, thereby avoiding the risk of compromising evaluation validity due to an excessive pursuit of comprehensiveness. On the other hand, within the integrated framework, core elements overlooked in some studies, such as flight punctuality and complaint management, are specifically supplemented, while the critical dimension of passenger satisfaction is refined and strengthened. Ultimately, a civil airport service quality evaluation indicator system is established, comprising four dimensions, passenger satisfaction, airline satisfaction, flight punctuality, and complaint management, with a total of 16 specific indicators. This ensures an optimal equilibrium between the completeness of the theoretical framework and the effectiveness of evaluation practices. The detailed indicators are presented in Table 2. The indicators in Table 2 are elaborated as follows.

Table 2 Evaluation indicator system for civil airport service quality

First-level indicator	Second-level indicator
Passenger satisfaction	Airport access traffic
	Check-in procedures
	Security check
	Baggage service
	Terminal facilities and environment
	WiFi service
	Airport business services
	Guidance service
	Information service
	Boarding and deboarding service
	Flight delay service
Airline satisfaction	Safety assurance
	Operational support
	Service support
Flight punctuality	Flight punctuality
Complaint management	Complaint management

(1) Passenger satisfaction. Passenger satisfaction is one of the key dimensions for measuring airport service quality, reflecting passengers' subjective perceptions and evaluations of their overall service experience at the airport. Passenger satisfaction is primarily measured through eleven indicators, as listed in Table 2. ① Airport access traffic refers to the evaluation of the convenience, completeness, and efficiency of transportation systems connecting the airport to surrounding areas. ② Check-in procedures pertain to the efficiency and convenience experienced by passengers during the check-in process. ③ Security check refers to the efficiency and compliance of airport security inspection procedures. ④ Baggage service encompasses the accuracy of baggage handling, the timeliness of baggage delivery, and the sophistication of the baggage tracking system. ⑤ Terminal facilities and environment encompass the cleanliness of the terminal building, appropriate temperature control, comfort of seating arrangements, and rational layout of commercial facilities. ⑥ WiFi service reflects the coverage and connection stability of the airport's wireless network. ⑦ Airport business services reflect the quality of amenities such as dining, shopping, and lounge facilities within the airport. ⑧ Guidance service and ⑨ information service measure the clarity of airport signage, as well as the responsiveness and accuracy of staff in addressing passenger inquiries. ⑩ Boarding and deboarding service involves the clarity of gate indications, the smoothness of the boarding process, and the efficiency of guidance during disembarkation. ⑪ Flight delay service reflects the airport's care for passengers and the adequacy of support measures provided during flight delays.

(2) Airline satisfaction. Airline satisfaction is another crucial dimension for measuring airport service quality, which reflects the quality of coopera-

tion between the airport and airlines. Airline satisfaction is mainly reflected by three aspects. ① Safety assurance covers the airport's safety management measures, the completeness of safety facilities, and emergency response capabilities, ensuring that airlines can carry out various operations safely and efficiently. ② Operational support involves the airport's flight departure punctuality rate, ground sliding efficiency, and the rationality of seat arrangement, directly affecting the operational efficiency and cost control of airlines. ③ Service support includes the airport's ground service support for airlines, the smoothness of cooperation and communication, and the timeliness of information sharing, reflecting the level of collaborative cooperation between the airport and airlines.

(3) Flight punctuality. Flight punctuality serves as an important manifestation of airport operational efficiency, reflecting the comprehensive capabilities of the airport in flight departure, ground support, air traffic management, etc. Flight punctuality is a composite manifestation of such indicators as flight punctuality rate, airport departure punctuality rate, early departure flight departure punctuality rate, flight delay handling efficiency, flight cancellation rate, the distribution of delay time, and the efficiency of flight recovery. The level of flight punctuality indicators directly affects passengers' travel experience and the operational efficiency of airlines.

(4) Complaint management. Complaint management underscores the airport's commitment to passengers' feedback, reflecting the efficiency and quality of complaint handling process. This includes the response time to complaints, the completion of time for complaint solution, the satisfaction of passengers with the handling results, and the implementation of follow-up improvement measures.

2.2 Weight calculation of evaluation indicators

This study selects nine airports as research subjects, Shanghai Pudong Airport, Guangzhou Baiyun Airport, Shenzhen Bao'an Airport, Guilin Liangjiang Airport, Wuxi Shuofang Airport, Xuzhou Guanyin Airport, Lianyungang Huaguoshan Airport, Zhoushan Putuoshan Airport, and Hotan Kungang Airport. Based on the civil airport service quality evaluation index system constructed in section 2.1, raw service quality data for the nine airports across 16 indicators can be collected from the 2023 Civil Airport Service Quality Evaluation Report published by the China Civil Airports Association in 2024. The specific data are presented in Table 3.

Each value in Table 3 represents the service quality score of the object (airport) listed in the column header with respect to the indicator specified in the row header. A higher score indicates better service quality for that particular indicator. For example, the observed value "88" in the second row and third column indicates that Shanghai Pudong Airport received a score of 88 for the quality of its airport access traffic services.

According to Table 3, the weights of each second-level indicator accounting for the primary indicator calculated by the CRITIC method are shown in Table 4.

Given the relatively minor disparities among the original data, the second-level indicator data are standardized to the range of [30, 90], and the standardization method is as follows.

(1) Determine the maximum value $\max\limits_i x_{ic}$ and minimum value $\min\limits_i x_{ic}$ under each indicator.

(2) Calculate the coefficient $k_c = (90-90) \Big/ \left(\max\limits_i x_{ic} - \min\limits_i x_{ic} \right)$.

(3) Obtain the standardized data $\hat{x}_{ic} = 30 + k_c \left(x_{ic} - \min\limits_i x_{ic} \right)$ The standardized indicator values are shown in Table 5.

The second-level indicator data are synthesized into the primary indicator data, and the calculation method is $x_{ij} = \eta_c \sum\limits_{c=1}^{p} \hat{x}_{ic}$. The final data of the four primary indicators are shown in Table 6.

The weights of the primary indicators are calculated by the CRITIC method, and the calculation results are shown in Table 7.

Table 3 Original data of evaluation for civil airport service quality in 2023

First-level indicator	Second-level indicator	Shanghai Pudong Airport	Guangzhou Baiyun Airport	Shenzhen Bao'an Airport	Guilin Liangjiang Airport	Wuxi Shuofang Airport	Xuzhou Guanyin Airport	Lianyungang Huaguoshan Airport	Zhoushan Putuoshan Airport	Hetia Kungang Airport
Passenger satisfactory	Airport access traffic	88	90	90	87	88	83	87	90	87
	Check-in procedures	87	92	91	88	84	88	92	89	92
	Security check	84	89	87	83	82	82	88	82	82
	Baggage service	89	88	85	82	83	82	90	85	88
	Terminal facilities and environment	81	91	91	84	82	81	90	84	82
	WiFi service	90	90	90	80	81	75	90	89	79
	Airport business services	91	85	85	76	75	73	79	77	75
	Guidance service	87	92	90	87	85	88	89	87	86
	Information service	86	93	91	89	82	86	94	91	86
	Boarding and deboarding service	80	90	88	88	83	85	89	88	87
	Flight delay service	96	77	68	71	70	70	69	70	78
Airline satisfaction	Safety assurance	94	97	96	93	98	94	92	93	93
	Operational support	94	96	94	92	97	92	92	92	94
	Service support	90	94	92	91	97	91	93	92	94
Flight punctuality	Flight punctuality	90	90	90	81	67	88	80	82	83
Complaint management	Complaint management	99	98	99	98	99	96	98	77	98

Table 4 Weights of each second-level indicator calculated by the CRITIC method

First-level indicator	Second-level indicator	Weight
Passenger satisfaction	Airport access traffic	0.089 8
	Check-in procedures	0.085 9
	Security check	0.077 3
	Baggage service	0.099 9
	Terminal facilities and environment	0.088 8
	WiFi service	0.083 7
	Airport business services	0.090 0
	Guidance service	0.067 0
	Information service	0.068 9
	Boarding and deboarding service	0.102 9
	Flight delay service	0.145 8
Airline satisfaction	Safety assurance	0.341 1
	Operational support	0.270 4
	Service support	0.388 5
Flight punctuality	Flight punctuality	1.000 0
Complaint management	Complaint management	1.000 0

Table 5 Standardized indicator values

First-level indicator	Second-level indicator	Shanghai Pudong Airport	Guangzhou Baiyun Airport	Shenzhen Bao'an Airport	Guilin Liangjiang Airport	Wuxi Shuofang Airport	Xuzhou Guanyin Airport	Lianyungang Huaguoshan Airport	Zhoushan Putuoshan Airport	Hetia Kungang Airport
Passenger satisfactory	Airport access traffic	72.9	90.0	90.0	64.3	72.9	30.0	64.3	90	64.3
	Check-in procedures	52.5	90.0	82.5	60.0	30.0	60.0	90.0	67.5	90.0
	Security check	47.1	90.0	72.9	38.6	30.0	30.0	81.4	30.0	30.0
	Baggage service	82.5	75.0	52.5	30.0	37.5	30.0	90.0	52.5	75.0
	Terminal facilities and environment	30.0	90.0	90.0	48.0	36.0	30.0	84.0	48.0	36.0
	WiFi service	90.0	90.0	90.0	50.0	54.0	30.0	90.0	86.0	46.0
	Airport business services	90.0	70.0	70.0	40.0	36.7	30.0	50.0	43.3	36.7
	Guidance service	47.1	90.0	72.9	47.1	30.0	55.7	64.3	47.1	38.6
	Information service	50.0	85.0	75.0	65.0	30.0	50.0	90.0	75.0	50.0
	Boarding and deboarding service	30.0	90.0	78.0	78.0	48.0	60.0	84.0	78.0	72.0
	Flight delay service	90.0	49.3	30.0	36.4	34.3	34.3	32.1	34.3	51.4
Airline satisfaction	Safety assurance	50.0	80.0	70.0	40.0	90.0	50.0	30.0	40.0	40.0
	Operational support	54.0	78.0	54.0	30.0	90.0	30.0	30.0	30.0	54.0
	Service support	30.0	64.3	47.1	38.6	90.0	38.6	55.7	47.1	64.3
Flight punctuality	Flight punctuality	90.0	90.0	90.0	66.5	30.0	84.8	63.9	69.1	71.7
Complaint management	Complaint management	90.0	87.3	90.0	87.3	90.0	81.8	87.3	30.0	87.3

Table 6 Primary indicator data

First-level indicator	Pudong Airport	Guangzhou Baiyun Airport	Shenzhen Bao'an Airport	Guilin Liangjiang Airport	Wuxi Shuofang Airport	Xuzhou Guanyin Airport	Lianyungang Huaguoshan Airport	Zhoushan Putuoshan Airport	Hetian Kungang Airport
Passenger satisfaction	64.0	80.4	70.3	49.9	40.2	39.4	72.1	58.2	54.6
Airline satisfaction	43.3	73.4	56.8	36.8	90.0	40.2	40.0	40.1	53.2
Flight punctuality	90.0	90.0	90.0	66.5	30.0	84.8	63.9	69.1	71.7
Complaint management	90.0	87.3	90.0	87.3	90.0	81.8	87.3	30.0	87.3

Table 7 Weights of primary indicators calculated by the CRITIC method

Indicator	Weight
Passenger satisfaction	0.23
Airline satisfaction	0.29
Flight punctuality	0.25
Complaint management	0.23

3 Service Quality Evaluation of Civil Airport

This study selected nine airports for in-depth analysis. Leveraging the established service quality evaluation index system for civil airports, a grey possibility clustering model is applied to assess their service performance. The analysis ultimately classified the nine airports into three distinct tiers, "Average" "Good" and "Excellent", which aptly reflect their relative service quality standings.

3.1 Construction of possibility functions

The nine airports under evaluation, Shanghai Pudong International Airport, Guangzhou Baiyun

International Airport, Shenzhen Bao'an International Airport, Guilin Liangjiang International Airport, Wuxi Shuofang Airport, Xuzhou Guanyin Airport, Lianyungang Huaguoshan Airport, Zhoushan Putuoshan Airport and Hotan Kungang Airport, are designated as 1—9 accordingly. The four indicators of passenger satisfaction, airline satisfaction, flight normality and complaint management are represented by numbers 1—4, and the three performace categories of "Average" "Good" and "Excellent" are represented by numbers 1, 2 and 3, respectively.

Through an analysis of the 2023 Civil Airport Service Quality Evaluation Report, it can be concluded that, solely based on the passenger satisfaction and airline satisfaction indicators, Guangzhou Baiyun Airport can be classified as "Excellent", while Guilin Liangjiang Airport can be categorized as "Average". Based on the IGPC model introduced in section 1, all applicable possibility functions for the passenger satisfaction and airline satisfaction indicators can be quantitatively derived by leveraging partially known clustering results.

However, for the flight punctuality and complaint management indicators, it is difficult to obtain partial known clustering results, making it infeasible to quantitatively determine the corresponding possibility functions using the IGPC model. Therefore, this study adoptes the forward GPC model and invites twenty experts specializing in airport service quality evaluation to participate in discussions. A consensus is ultimately reached to construct the possibility functions for the flight punctuality and complaint management indicators, which are difined as

$$f_3^1(x_{i3})=\begin{cases}0 & x_{i3}\notin(0,56)\\ \dfrac{x_{i3}}{28} & x_{i3}\in(0,28]\\ \dfrac{56-x_{i3}}{28} & x_{i3}\in(28,56)\end{cases}$$

$$f_3^2(x_{i3})=\begin{cases}0 & x_{i3}\notin(28,84)\\ \dfrac{x_{i3}-28}{28} & x_{i3}\in(28,56]\\ \dfrac{84-x_{i3}}{28} & x_{i3}\in(56,84)\end{cases}$$

$$f_3^3(x_{i3})=\begin{cases}0 & x_{i3}\notin(56,112)\\ \dfrac{x_{i3}-56}{28} & x_{i3}\in(56,84]\\ \dfrac{112-x_{i3}}{28} & x_{i3}\in(84,112)\end{cases}$$

$$f_4^1(x_{i4})=\begin{cases}0 & x_{i4}\notin(0,60)\\ \dfrac{x_{i4}}{30} & x_{i4}\in(0,30]\\ \dfrac{60-x_{i4}}{30} & x_{i4}\in(30,60)\end{cases}$$

$$f_4^2(x_{i4})=\begin{cases}0 & x_{i4}\notin(30,90)\\ \dfrac{x_{i4}-30}{30} & x_{i4}\in(30,60]\\ \dfrac{90-x_{i4}}{30} & x_{i4}\in(60,90)\end{cases}$$

$$f_4^3(x_{i4})=\begin{cases}0 & x_{i4}\notin(60,120)\\ \dfrac{x_{i4}-60}{30} & x_{i4}\in(60,90]\\ \dfrac{120-x_{i4}}{30} & x_{i4}\in(90,120)\end{cases}$$

Next, it is necessary to construct the IGPC model to solve all feasible possibility functions under the passenger satisfaction and airline satisfaction indicators that satisfy the partially known clustering results. If $\lambda_1^0=\lambda_2^0=0$, $\boldsymbol{\eta}=\left[\dfrac{23}{52},\dfrac{29}{52}\right]^{\mathrm{T}}$, the unknown parameters in this example are d_1 and d_2. Using Theorem 3, the interval satisfied by d_1 and d_2, and the given results generated by their inequality relations are calculated.

Guangzhou Baiyun International Airport has been classified as "Excellent". Utilizing Theorem 3 and the IGPC model, a relationship is derived and that must be satisfied. The details of which are presented in Table 8. "Non-existent" in Table 8 means that d_1 and d_2 do not have a feasible relationship within the corresponding range. Conversely both d_1 and d_2 exhibit feasibility within the designated interval and are labeled "All feasible".

Guilin Liangjiang International Airport is classified as "Average". The relationship between d_1 and d_2 is finally calculated by IGPC model as shown in Table 9.

By calculating the intersection of Tables 8,9, a feasible relationship can be obtained that satisfies the sum of the given output results of the two airports, as shown in Table 10, where the symbol "∩" means that d_1 and d_2 must satisfy two inequations in the cell at the same time.

Table 8 Feasible relationship between d_1 and d_2 for Guangzhou Baiyun Airport

Condition	$0<d_1\leqslant 20.1$	$20.1<d_1\leqslant 26.8$	$26.8<d_1\leqslant 40.2$	$d_1>40.2$
$0<d_2\leqslant 18.35$	Non-existent	All feasible	$26.8<d_1<32.16$	Non-existent
$18.35<d_2\leqslant 24.47$	All feasible	All feasible	$\frac{36.984}{d_1}-\frac{21.286}{d_2}>0.01$	Non-existent
$24.47<d_2\leqslant 36.7$	$24.47<d_2<29.36$	$\frac{42.572}{d_2}-\frac{18.492}{d_1}>0.53$	$\frac{18.492}{d_1}+\frac{21.286}{d_2}>1.3$	Non-existent
$d_2>36.7$	Non-existent	Non-existent	Non-existent	Non-existent

Table 9 Feasible relationship between d_1 and d_2 for Guilin Liangjiang International Airport

Condition	$0<d_1\leqslant 12.475$	$12.475<d_1\leqslant 16.63$	$16.63<d_1\leqslant 24.95$	$24.95<d_1\leqslant 49.9$	$d_1>49.9$
$0<d_2\leqslant 9.2$	Non-existent	Non-existent	Non-existent	$33.267<d_1\leqslant 49.9$	all feasible
$9.2<d_2\leqslant 12.27$	Non-existent	Non-existent	Non-existent	$33.267<d_1\leqslant 49.9\cap\frac{10.672}{d_2}-\frac{11.477}{d_1}>0.7$	$\frac{11.477}{d_1}+\frac{10.672}{d_2}>0.92$
$12.27<d_2\leqslant 18.4$	Non-existent	Non-existent	Non-existent	$\frac{10.672}{d_2}-\frac{22.954}{d_1}>0.18\cap\frac{11.477}{d_1}+\frac{10.672}{d_2}<1.04$	$\frac{10.672}{d_2}-\frac{11.477}{d_1}<0.58\cap\frac{11.477}{d_1}+\frac{10.672}{d_2}>0.87$
$18.4<d_2\leqslant 36.8$	$24.53<d_2\leqslant 36.8$	$24.53<d_2\leqslant 36.8\cap\frac{11.477}{d_1}-\frac{10.672}{d_2}>0.34$	$\frac{21.344}{d_2}-\frac{11.477}{d_1}<0.18\cap\frac{11.477}{d_1}+\frac{10.672}{d_2}<1.04$	$\frac{11.477}{d_1}+\frac{10.672}{d_2}<0.78$	$\frac{21.344}{d_2}-\frac{11.477}{d_1}<0.87$
$d_2>36.8$	All feasible	$\frac{11.477}{d_1}+\frac{10.672}{d_2}>0.92$	$\frac{11.477}{d_1}-\frac{10.672}{d_2}<0.46\cap\frac{11.477}{d_1}+\frac{10.672}{d_2}>0.69$	$\frac{22.954}{d_1}-\frac{10.672}{d_2}<0.69$	All feasible

Table 10 Feasible d_1 and d_2 relationships between two airports

Interval between d_1 and d_2	Inequations should be satisfied
$26.8<d_1\leqslant 40.2\cap 18.4<d_2\leqslant 24.47$	$\frac{11.477}{d_1}+\frac{10.672}{d_2}<0.78\cap\frac{36.984}{d_1}-\frac{21.286}{d_2}>0.01$
$0<d_1\leqslant 12.475\cap 24.53<d_2<29.36$	All feasible
$12.475<d_1\leqslant 16.63\cap 24.53<d_2<29.36$	$\frac{11.477}{d_1}-\frac{10.672}{d_2}>0.34$
$16.63<d_1\leqslant 20.1\cap 24.47<d_2<29.36$	$\frac{21.344}{d_2}-\frac{11.477}{d_1}<0.18\cap\frac{11.477}{d_1}+\frac{10.672}{d_2}<1.04$
$20.1<d_1\leqslant 24.95\cap 24.47<d_2\leqslant 36.7$	$\frac{21.344}{d_2}-\frac{11.477}{d_1}<0.18\cap\frac{42.572}{d_2}-\frac{18.492}{d_1}>0.53$
$24.95<d_1\leqslant 26.8\cap 24.47<d_2\leqslant 36.7$	$\frac{11.477}{d_1}+\frac{10.672}{d_2}<0.78\cap\frac{42.572}{d_2}-\frac{18.492}{d_1}>0.53$
$26.8<d_1\leqslant 40.2\cap 24.47<d_2\leqslant 36.7$	$\frac{11.477}{d_1}+\frac{10.672}{d_2}<0.78\cap\frac{18.492}{d_1}+\frac{21.286}{d_2}>1.3$

Using feasible $d_1=32$ and $d_2=26$ from Table 10, the possibility functions for the two critical indicators passenger satisfaction and airline satisfaction, are constructed as

$$f_1^1(x_{i1})=\begin{cases}0 & x_{i1}\notin(0,64)\\ \dfrac{x_{i1}}{32} & x_{i1}\in(0,32]\\ \dfrac{64-x_{i1}}{32} & x_{i1}\in(32,64)\end{cases}$$

$$f_1^2(x_{i1})=\begin{cases}0 & x_{i1}\notin(32,96)\\ \dfrac{x_{i1}-32}{32} & x_{i1}\in(32,64]\\ \dfrac{96-x_{i1}}{32} & x_{i1}\in(64,96)\end{cases}$$

$$f_1^3(x_{i1})=\begin{cases}0 & x_{i1}\notin(64,128)\\ \dfrac{x_{i1}-64}{32} & x_{i1}\in(64,96]\\ \dfrac{128-x_{i1}}{32} & x_{i1}\in(96,128)\end{cases}$$

$$f_2^1(x_{i2})=\begin{cases}0 & x_{i2}\notin(0,52)\\ \dfrac{x_{i2}}{26} & x_{i2}\in(0,26]\\ \dfrac{52-x_{i2}}{26} & x_{i2}\in(26,52)\end{cases}$$

$$f_2^2(x_{i2})=\begin{cases}0 & x_{i2}\notin(26,78)\\ \dfrac{x_{i2}-52}{26} & x_{i2}\in(26,52]\\ \dfrac{78-x_{i2}}{26} & x_{i2}\in(52,78)\end{cases}$$

$$f_2^3(x_{i2})=\begin{cases}0 & x_{i2}\notin(52,104)\\ \dfrac{x_{i2}-52}{26} & x_{i2}\in(52,78]\\ \dfrac{104-x_{i2}}{26} & x_{i2}\in(78,104)\end{cases}$$

3.2 Clustering results and analysis

Based on the constructed possibility degree functions, the grey clustering coefficient matrix for the nine airports is calculated as

$$\sum=(\sigma_i^k)=\begin{bmatrix}\sigma_1^1 & \sigma_1^2 & \sigma_1^3\\ \sigma_2^1 & \sigma_2^2 & \sigma_2^3\\ \sigma_3^1 & \sigma_3^2 & \sigma_3^3\\ \sigma_4^1 & \sigma_4^2 & \sigma_4^3\\ \sigma_5^1 & \sigma_5^2 & \sigma_5^3\\ \sigma_6^1 & \sigma_6^2 & \sigma_6^3\\ \sigma_7^1 & \sigma_7^2 & \sigma_7^3\\ \sigma_8^1 & \sigma_8^2 & \sigma_8^3\\ \sigma_9^1 & \sigma_9^1 & \sigma_9^1\end{bmatrix}=\begin{bmatrix}0.10 & 0.42 & 0.43\\ 0.00 & 0.18 & 0.76\\ 0.00 & 0.42 & 0.53\\ 0.27 & 0.43 & 0.30\\ 0.40 & 0.08 & 0.39\\ 0.31 & 0.27 & 0.41\\ 0.13 & 0.53 & 0.34\\ 0.40 & 0.48 & 0.12\\ 0.07 & 0.57 & 0.36\end{bmatrix}$$

Based on the clustering coefficient matrix, the final service quality clustering evaluation results for the nine airports are derived and are systematically presented in Table 11. As seen in Table 11, among the nine airports assessed, Shanghai Pudong International Airport, Guangzhou Baiyun International Airport, Shenzhen Bao'an International Airport, and Xuzhou Guanyin Airport achieves "Excellent". Other airports, including Guilin Liangjiang International Airport, Lianyungang Huaguoshan Airport, Zhoushan Putuoshan Airport, and Hetian Kungang Airport, are classified as "Good". In contrast, Wuxi Shuofang Airport underperforms comparatively, receiving an "Average" rating.

Table 11 Final clustering results of civil airport service quality assessment

Shanghai Pudong International Airport	Guangzhou Baiyun International Airport	Shenzhen Bao'an International Airport	Guilin Liangjiang International Airport	Wuxi Shuofang Airport	Xuzhou Guanyin Airport	Lianyungang Huaguoshan Airport	Zhoushan Putuoshan Airport	Hetian Kungang Airport
Excellent	Excellent	Excellent	Good	Average	Excellent	Good	Good	Good

3.3 Model comparison

In this section, we compare the proposed CRITIC-Bidirectional GPC model with the traditional forward GPC model.

In section 3.1, we utilize the IGPC model to quantitatively determine the possibility functions for both the passenger satisfaction and airline satisfaction indicators, based on partially known clustering results. In this section, we entirely rely on the forward GPC model and again invite 20 experts in airport service quality evaluation to participate in discussions. A consensus is ultimately reached, leading to the construction of the possibility functions for the passenger satisfaction and airline satisfaction indicators as

$$f_1^1(x_{i1})=\begin{cases}0 & x_{i1}\notin(0,50)\\ \dfrac{x_{i1}}{25} & x_{i1}\in(0,25]\\ \dfrac{50-x_{i1}}{25} & x_{i1}\in(25,50)\end{cases}$$

$$f_1^2(x_{i1})=\begin{cases}0 & x_{i1}\notin(25,75)\\ \dfrac{x_{i1}-25}{25} & x_{i1}\in(25,50]\\ \dfrac{75-x_{i1}}{25} & x_{i1}\in(50,75)\end{cases}$$

$$f_1^3(x_{i1})=\begin{cases}0 & x_{i1}\notin(50,100)\\ \dfrac{x_{i1}-50}{25} & x_{i1}\in(50,75]\\ \dfrac{100-x_{i1}}{25} & x_{i1}\in(75,100)\end{cases}$$

$$f_2^1(x_{i2})=\begin{cases}0 & x_{i2}\notin(0,66)\\ \dfrac{x_{i2}}{33} & x_{i2}\in(0,33]\\ \dfrac{66-x_{i2}}{33} & x_{i2}\in(33,66)\end{cases}$$

$$f_2^2(x_{i2})=\begin{cases}0 & x_{i2}\notin(33,99)\\ \dfrac{x_{i2}-33}{33} & x_{i2}\in(33,66]\\ \dfrac{66-x_{i2}}{33} & x_{i2}\in(66,99)\end{cases}$$

$$f_2^3(x_{i2})=\begin{cases}0 & x_{i2}\notin(66,132)\\ \dfrac{x_{i2}-66}{33} & x_{i2}\in(66,99]\\ \dfrac{132-x_{i2}}{33} & x_{i2}\in(99,132)\end{cases}$$

Under the condition that both $f_3^k(x_{i3})$ and $f_4^k(x_{i4})$ remain unchanged, the clustering results can be obtained, as shown in Table 12. As shown in Table 12, there are inconsistencies in the clustering results of Wuxi Shoufang Airport, Lianyungang Huaguoshan Airport and Zhoushan Putuoshan Airport between the final clusters obtained using the CRITIC-bidirectional GPC model and those computed with the forward GPC model. In the CRITIC-bidirectional GPC model, the possibility functions for two indicators are derived quantitatively based on partially known clustering results, whereas in the forward GPC model, all four possibility functions are obtained through subjective expert judgment. This indicates that decision-makers' subjective preferences significantly influence the clustering outcomes, and the CRITIC-bidirectional GPC model can, to some extent, mitigate such subjective influence.

Table 12 Comparison of the clustering results between the two models

Model	Shanghai Pudong International Airport	Guangzhou Baiyun International Airport	Shenzhen Bao'an International Airport	Guilin Liangjiang International Airport	Wuxi Shuofang Airport	Xuzhou Guanyin Airport	Lianyungang Huaguoshan Airport	Zhoushan Putuoshan Airport	Hetian Kungang Airport
CRITIC-bidirectional GPC	Excellent	Excellent	Excellent	Good	Average	Excellent	Good	Good	Good
Forward GPC	Excellent	Excellent	Excellent	Good	Excellent	Excellent	Excellent	Average	Good

3.4 Countermeasures and suggestions

To further enhance service quality across all assessed airports, this study summarizes performance rankings and proposes tailored improvement strategies for the nine airports.

For airports rated as "Excellent", including Shanghai Pudong International Airport, Guangzhou Baiyun International Airport, Shenzhen Bao'an International Airport, and Xuzhou Guanyin Airport, it is imperative to sustain and reinforce their service advantages while addressing identified weaknesses through targeted interventions. For example, Shanghai Pudong International Airport should prioritize upgrades of terminal facilities, environments enhancements and WiFi service improvements. In contrast, Xuzhou Guanyin Airport requires a holistic service improvement, with a particular focus on streamlining ground transportation accessibility and check-in procedures. Furthermore, all airports are strongly encouraged to adopt intelligent service solutions, such as self-check-in kiosks and AI-driven security systems, thereby elevating passenger experience.

For airports categorized as "Good", including Guilin Liangjiang International Airport, Lianyungang Huaguoshan Airport, Zhoushan Putuoshan Airport, and Hetian Kungang Airport, strategic efforts should focus on refining service granularity and elevating passenger experience while preserving existing strengths. Specifically, Lianyungang Huaguoshan Airport is advised to consolidate its competitive edge in inquiry services and complaint resolution mechanisms. Conversely, Hetian Kungang Airport needs to promote infrastructure construction and service process optimization, with the dual objectives of minimizing passenger waiting times and enhancing comfort levels.

Wuxi Shuofang Airport, categorized as "Average", needs comprehensive service improvements. This requires implementing staff training programs to refine service execution, alongside establishing quality management system to standardize service assurance protocols. Concurrently, cultivating a regionally distinctive service culture will strengthen brand identity, while talent recruitment pipelines and optimized incentive mechanisms should be prioritized to enhance workforce professionalism. Additionally, strengthen infrastructure construction, including terminal upgrades and service workflow optimization, is critical to reducing operational bottlenecks. The integration of smart technologies, such as AI-driven passenger flow management and automated baggage systems, will further enhance service efficiency. Through these coordinated measures, Wuxi Shuofang Airport can improve service quality and passenger satisfaction, positioning itself for tier advancement in future evaluations.

4 Conclusions

To establish a scientifically rigorous evaluation system for civil airport service quality, this study develops a multidimensional assessment framework encompassing passenger satisfaction, airline satisfaction, flight punctuality, and complaint management. A detailed analysis is conducted to define specific components and indicator categories within each dimension. The CRITIC method is employed to determine objective indicator weights based on inter-indicator correlations, thereby minimizing subjective bias.

In order to address the challenge of defining possibility functions in conventional GPC models, this research introduces IGPC model. By leveraging partially known clustering outcomes, the possibility function is quantitatively derived through algebraic computations. Subsequently, a bidirectional GPC model is applied to evaluate service quality across nine airports, Shanghai Pudong International Airport, Guangzhou Baiyun International Airport, Shenzhen Bao'an International Airport, Guilin Liangjiang International Airport, Wuxi Shuofang Airport, Xuzhou Guanyin Airport, Lianyungang Huaguoshan Airport, Zhoushan Putuoshan Airport, and Hetian Kungang Airport.

Meanwhile, this study proposes targeted improvement strategies based on the evaluation results. The findings not only provide systematic methodological support for civil airport service quality assessment, but also offer empirical evidence for policy formulation and continuous service optimization. This study thus demonstrates significant practical relevance, contributing to the enhancement of airport service quality and passenger experience.

References

[1] LIANG Xiaozhen, LI Jianqiang, LIU Jianhua, et al. Study on the multilayer airport system in China based on evaluation of airport competitiveness[J]. Management Review, 2016, 28(12): 116-126. (in Chinese)

[2] LIU Yumin, JIN Linlin. An evaluation of airport passenger service quality based on modified SERVQUAL model[J]. Economic Survey, 2017, 34(6): 81-86. (in Chinese)

[3] BAI Zhao, WANG Mengyang, WANG Shenwu, et al. Evaluation of short distance transport service quality of airports based on game theory[J]. Science Technology and Industry, 2023, 23(20): 119-123. (in Chinese)

[4] ZHU Changzheng, GU Peixiang, XU Zhigang. Domestic airport competitiveness evaluation based on entropy weight TOPSIS method[J]. Journal of Beijing Jiaotong University, 2019, 43(2): 124-130. (in Chinese)

[5] HU Jie, BAO Fan. Airport operational efficiency evaluation based on combined weighting—TOPSIS model[J]. Journal of System Simulation, 2023, 35(12): 2570-2581. (in Chinese)

[6] LI Mingjie, GAO Jiayue. Evaluation of airport service quality based on topsis-Bayesian[J]. Science Technology and Industry, 2025, 25(2): 33-38. (in Chinese)

[7] LIAO Wang, CAO Xiaoshu, LI Tao, et al. The influence of airport service quality on air travel choices: A case study of the Guangdong-Hong Kong-Macao greater bay area[J]. Tropical Geography, 2024, 44(2):

195-211. (in Chinese)

[8] CHU Yanchang, AI Yanbo. Research on airport passenger travel experience based on SOR-SEM model[J]. Price (Theory & Practice), 2024(5): 203-207. (in Chinese)

[9] REN Wenjia, ZHOU Jiemin, YANG Yichuan. Influencing factors of airport passenger service quality based on structural equation modeling[J]. Journal of Civil Aviation, 2023, 7(6): 31-35. (in Chinese)

[10] WANG Yiru, LIU Xuejing, HAN Xi, et al. A study on the construction of a logistics service quality evaluation system for airport cargo terminals based on the WSR model[J]. China Logistics & Purchasing, 2022 (23): 56-58. (in Chinese)

[11] PAMUCAR D, ÖZÇALıCı M, GURLER H E. Evaluation of the efficiency of world airports using WENSLO-ARTASI and Monte-Carlo simulation[J]. Journal of Air Transport Management, 2025, 124: 102749.

[12] JIA X B, BUYLE S, MACÁRIO R. Developing an airport sustainability evaluation index through composite indicator approach[J]. Journal of Air Transport Management, 2023, 113: 102469.

[13] GRYNIA D, KADZIŃSKI M, STAMENKOVIĆ M. Attaining robust performance targets in data envelopment analysis with application to efficiency evaluation of airports[J]. Computers & Industrial Engineering, 2024, 190: 110065.

[14] WANG Z W, SONG W K. Sustainable airport development with performance evaluation forecasts: A case study of 12 Asian airports[J]. Journal of Air Transport Management, 2020, 89: 101925.

[15] KUO M S, LIANG G S. Combining VIKOR with GRA techniques to evaluate service quality of airports under fuzzy environment[J]. Expert Systems with Applications, 2011, 38(3): 1304-1312.

[16] ZHANG Zairan. A study on airport competitiveness based on systematic cluster analysis[J]. China Storage & Transport, 2024(4): 76-77. (in Chinese)

[17] YANG Changqi, MA Mengyao, HAO Mingtong, et al. Based on AHP and the K-means clustering of small and medium-sized airport ATC operation guarantee classification[J]. China Transportation Review, 2020, 42(9): 37-42, 126. (in Chinese)

[18] WANG Ru, OUYANG Jie, LI Peng. Evaluation of service level of airport terminal curbside based on grey clustering method[J]. Journal of Dalian Jiaotong University, 2017, 38(1): 12-16, 37. (in Chinese)

[19] PAUWELS J, BUYLE S, DEWULF W. Insights in diversity: A latent profile cluster analysis of regional airports in Western Europe[J]. Research in Transportation Business & Management, 2025, 63: 101477.

[20] GAO Y. What is the busiest time at an airport clustering U. S. hub airports based on passenger movements[J]. Journal of Transport Geography, 2021, 90: 102931.

[21] URBAN M, KLEMM M, PLOETNER K O, et al. Airline categorisation by applying the business model canvas and clustering algorithms[J]. Journal of Air Transport Management, 2018, 71: 175-192.

[22] WEN C H, CHEN W Y. Using multiple correspondence cluster analysis to map the competitive position of airlines[J]. Journal of Air Transport Management, 2011, 17(5): 302-304.

[23] WANG H, WANG D A, WANG P, et al. A novel quality risk evaluation framework for complex equipment development integrating PHFS-QFD and grey clustering[J]. Grey Systems: Theory and Application, 2024, 14(1): 144-159.

[24] KARIMI T, AHMADIAN M. Grey clustering and grey ranking of bank branches based on grey efficiency[J]. Grey Systems: Theory and Application, 2024, 14(1): 1-20.

[25] LUO D, YE L L, SUN D C. Risk evaluation of agricultural drought disaster using a grey cloud clustering model in Henan Province, China[J]. International Journal of Disaster Risk Reduction, 2020, 49: 101759.

[26] XIE N M, SU B T, CHEN N L. Construction mechanism of whitenization weight function and its application in grey clustering evaluation[J]. Journal of Systems Engineering and Electronics, 2019, 30(1): 121-131.

[27] AKRAM M, ZAHID S, DEVECI M. Enhanced CRITIC-REGIME method for decision making based on Pythagorean fuzzy rough number[J]. Expert Systems with Applications, 2024, 238: 122014.

[28] WANG J J, CAI Y, LI R X, et al. A novel clustering approach based on grey possibility functions for multidimensional systems[J]. Applied Mathematical Modelling, 2022, 111: 644-663.

[29] DENG Julong. On basic methods of grey system[M]. Wuhan: Press of Huazhong University of Science and Technology, 1986. (in Chinese)

[30] YIN C W, YI P, ZHAO Z L. Grey cluster evaluation of prescribed performance function based on center point mixed possibility function [J]. The Journal of Grey System, 2025, 37(5): 129-136.

Acknowledgements The authors would like to express their sincere appreciation to the anonymous reviewers for their constructive comments which improved the quality of the paper. The authors are grateful for the financial support supplied by the National Natural Science Foundation of China (Nos.72571136, 72271120), and the Ministry of Education of the People's Republic of China Humanities and Social Science project (No.24YJA630087).

Authors

The first author Ms. **ZU Lili** received her M.S. degree in project management engineering from Nanjing University of Aeronautics and Astronautics(NUAA), Nanjing, China, in 2011. She is currently an associate research fellow with NUAA, and performs research in the fields of management science and engineering, human resource management, and grey systems theory.

The corresponding author Dr. **WANG Junjie** received his M. S. and Ph. D. degrees in management science and engineering from NUAA, Nanjing, China, in 2014 and 2018, respectively. He is currently an associate professor with Department of Management Science and Engineering, NUAA, and performs research in the fields of energy and environmental evaluation, big data analysis, and intelligent forecasting.

Author contributions Ms. **ZU Lili** designed the outline, constructed the models, analyzed the case, and wrote the original draft. Mr. **LI Xun** provided data, constructed the indicator system, and conducted analysis. Dr. **WANG Junjie** improved the models and contributed to data. Prof. **DANG Yaoguo** summarized the research. All authors commented on the manuscript draft and approved the submission.

Competing interests The authors declare no competing interests.

(Production Editor: ZHANG Bei)

基于CRITIC-双向灰色可能度聚类模型的民用机场服务质量评价

祖丽莉，李 迅，王俊杰，党耀国

(南京航空航天大学经济与管理学院,南京 211106,中国)

摘要:本研究旨在构建一套科学合理的民航机场服务质量评价方法与框架,为提升航空业服务水平提供理论基础和实践指导。首先构建了CRITIC-双向灰色可能度聚类模型,利用CRITIC法确定指标的客观权重,并集成正向灰色可能度聚类模型和反向灰色可能度聚类模型,从双向视角定量求解可能度函数。随后,从旅客满意度、航空公司满意度、航班准点和投诉管理4个维度构建了包含16个具体指标的民航机场服务质量评价体系。最后,将该模型应用于国内9个民用机场的实证评价,并根据聚类结果提出针对性对策。研究结果显示,在所选取的9个机场中,上海浦东、广州白云、深圳宝安、徐州观音等机场表现出较高的服务质量水平,而无锡硕放机场表现一般。研究结论表明,相比传统灰色聚类模型,所提出的模型平衡了指标赋权的客观性、可能度函数构建的科学性以及计算过程的简便性,评价结果更加客观准确,具有显著的理论与实践意义。

关键词:CRITIC法;灰色聚类;可能度函数;民用机场;服务质量评价

研究亮点:

1. 创新性地提出了CRITIC-双向灰色可能度聚类模型,实现了多种方法的优势互补,解决了传统灰色聚类模型中可能度函数构造主观性强、计算复杂的问题。
2. 引入CRITIC法,综合考虑指标数据的对比强度和冲突性,有效避免了高相关冗余指标的重复计算,解决了灰色聚类模型中权重确定困难且主观的问题,使权重分配更具说服力。
3. 针对现有民航机场服务质量评价研究中指标信息重叠和关键维度缺失的问题,兼顾旅客与航空公司双重需求,构建了包含16个核心指标的评价体系,提升了评价结果的全面性与准确性。