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Research Article

Analysis on the Evaluation of Airport Intelligence Level and Its Obstacle Diagnosis Based on DPSIR-TOPSIS Model

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Combined with the actual situation of smart airport construction, five listed airports in China are used as research objects, and based on the Driving Force-Pressure-State-Impact-Response (DPSIR) conceptual model, 24 indicators were selected to form the evaluation system. The Analytic Hierarchy Process (AHP) method and entropy weight method were used to assign comprehensive weights to the indicators, and then, the Technique for Order Preference by Similarity to an Ideal Solution (TOPSIS) method was introduced to evaluate the level of intelligence, combined with the coupling coordination model to analyze the relationship between the two subsystems, by introducing the obstacle model to diagnose and analyze the influencing factors; finally, based on the analysis results, optimization suggestions are provided for the airport intelligence level. The results show that the intelligence level of each airport is between high (IV) and average (II). The pairwise coupling degree of each subsystem is higher than 0.91 and presents a benign coupling. The airport intelligence level is mainly hindered by the proportion of nonaviation revenue, the average travel time of passengers, and the regional fiscal revenue growth rate. The research results are of great significance to the construction of smart airport and the development of regional economy and transportation.

1. Introduction

Since the 21st century, smart technology has become a research hotspot with the development of artificial intelligence, Internet of Things, sensors, cloud computing, and other technologies and has been widely used in civil aviation [1, 2]. The high-quality development of civil aviation in the new era requires accelerating the construction of "four types of airports" with "safe airport, green airport, smart airport, and humanistic airport" as the core, striving to build a modern civil airport integrating internal quality and external taste and paying attention to the high-quality development of quality, efficiency, and benefit. Among them, smart airport is the key support and implementation path to promote the construction of the "four types of airports." Therefore, it is under the condition that the development of smart airports has become a major trend in the development of China's air transport industry. The accurate assessment of the level of airport intelligence has become a hot issue for research at present.

Research on smart airports is scarce and mainly remains in qualitative analysis and theoretical research on related technologies. There is still no unified definition of smart airports in the industry. As an extension of the concept of smart cities, smart airports can still draw on the relevant concepts of smart cities in the definition and construction issues surrounding smart airports [3]. In terms of existing research on the concept of smart airport technology, Rajapaksha and Jayasuriya [4] analyzed empirical indicators for implementing smart airport applications based on the actual impact of airport operations; Zapolskyt et al. [5] assessed the extent to which smart airport technology has been implemented in Egyptian airports and analyzed the factors that constrain the development of smart airports; in terms of the evaluation system's construction method, Xiang and Ren [6] used the analytical network process to construct a network diagram of the smart city evaluation system and analyzed the mutual influence relationship between indicators; De-Dao and Qiao [7] constructed a set of smart city evaluation index system from the perspective of smart infrastructure, smart governance, smart life, smart economy, smart environment, and smart planning and construction; other scholars [8] used the DPSIR model and focused on the influence mechanism among the factors. In terms of evaluation methods, Voda and Genete [9] used principal component analysis to study the level of smart city development in 26 European countries and found that development investment and gross domestic product were important influencing factors for the smart development of cities; Kai and Bao [10] proposed a method for evaluating the development potential of smart cities based on grey relations and BP neural networks and proved the scientific nature of the results; Li et al. [11] used TOPSIS method and entropy power method to evaluate the development level of Kunming's smart city and found problems in the process of smart city development. In addition to the above research methods, there are also multiobjective analysis method [12], fuzzy comprehensive evaluation method [13], projection tracing method [14], and so on.

In summary, existing theories have largely improved the research on concepts, index systems, and evaluation methods related to smart airports. However, there are still some shortcomings, such as in the research object, researchers mainly focus on the operation, service and construction of smart airports, etc. Although the research surface is relatively extensive, few scholars have studied the interactions between the intrinsic factors affecting the development of smart airports; in the evaluation method, the fuzzy comprehensive analysis method tends to cause the neglect of secondary factors, resulting in the evaluation results not being meticulous enough. In view of this, this paper adopts DPSIR model-based evaluation index system, combines AHP method and entropy weight method to comprehensively assign weight, uses TOPSIS method to evaluate and study the intelligence level of five listed airports in China, and diagnoses the influencing factors through obstacle degree model to put forward optimization suggestions for their intelligence development, in order to provide reference for the construction of future smart airport.

2. Index System Construction and Source of Data

2.1. Construction of the Index System. The research object of airport intelligence is the complex airport transportation system, and the research scope is not only limited to the airport but also to the cities connected with it. The evaluation index system under the DPSIR [15] framework enables effective monitoring of the continuous feedback mechanism between various types of indicators. This enables it to seek effective ways to coordinate local economic development, intelligent technology development, and transportation service enhancement [16]. Using this model, the airport intelligence level system is divided into five parts: driving force, pressure, state, impact, and response. The establishment of airport intelligence horizontal DPSIR model is shown in Figure 1.

The core of smart airport lies in "intelligence." In fact, it is an extended application of the concept of "smart city" [17]. Based on the requirements for the construction of smart airports in the "Outline of Action for the Construction of Four Types of Airports in China Civil Aviation (2020-2035)" and the "Guidelines for the Construction of Four Types of Airports" and taking into account the current social and economic development of the city where the airport is located and the characteristics of the intelligence level construction, 24 evaluation indicators are selected from five dimensions: driving force, pressure, state, impact, and response, to build an evaluation index system for the airport intelligence level (shown in Table 1, see below for the method of determining the weights).

The driving force subsystem of airport intelligence level come from social, economic, and demand factors. Among them, gross domestic product (GDP) per capita and regional fiscal revenue growth rate measure the regional economic development driver; the number of permanent residents and the proportion of tertiary industry characterize the social state driver; annual air passenger volume and annual air cargo volume reflect the airport demand driver.

The pressure subsystem of airport intelligence level comes from the factors of resources and travel. The hours of work per person in ground service and labor cost ratio represent the pressure on airport resource allocation; the air-rail intermodal transport level and the average travel time of passengers represent the pressure on airports to facilitate passenger travel.

The state subsystem of airport intelligence characterizes the current construction intelligence of the airport. Among them, fixed assets and intangible assets reflect the overall condition of the existing hardware and software of the airport; the number of self-service consignment devices and the number of self-service check-in devices reflect the status of the airport's intelligent infrastructure; the free Wi-Fi coverage and the number of passenger service applets reflect the status of the airport's information technology.

The impact subsystem of airport intelligence level is the impact generated by airport intelligence building. The total airport revenue and the proportion of nonaviation revenue represent the impact of airport intelligence on airport revenue and revenue structure, the passenger satisfaction reflects the impact on passenger travel experience, and the comprehensive environmental protection level reflects the impact on airport sustainability.

The response subsystem of the airport intelligence level is the response of the measures taken for the airport intelligence construction. The degree of propaganda of intelligence concept and intangible assets and research and development (R&D) investment characterize the response to airport intelligence promotion; the degree of policy support and fixed asset investment reflect the response to airport intelligence planning.

2.2. Source of Data. The data in this paper is obtained from the statistical yearbooks of the provinces and cities where China's listed airports are located in 2020 and annual reports publish by each airport and literature such as the Civil Aviation Airport Production Statistics Bulletin, as well as field visits and questionnaire surveys.

3. Empirical Analysis

3.1. Overview of Listed Airports in China and Their Regions. The five listed airports in China, A, B, C, D, and E, are located in

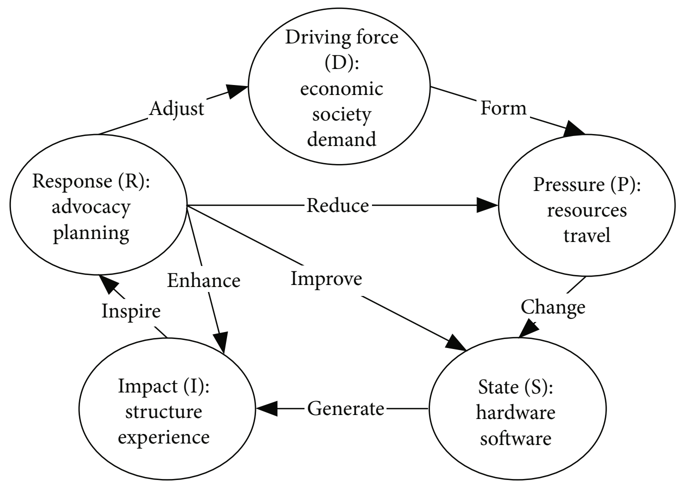

Figure 1: Framework for the airport intelligence level based on the DPSIR model.

Table 1: Evaluation index and weights for airport intelligence level.

Target layer	Subsystem layer	Indicator layer	Nature	AHP method	Entropy method	Combined weights
Airport intelligence level evaluation	Driving force	GDP per capita	+	0.0617	0.0361	0.0489
		Regional fiscal revenue growth rate	+	0.0543	0.0528	0.0536
		Number of permanent residents	+	0.0580	0.0273	0.0426
		Proportion of tertiary industry	+	0.1109	0.0495	0.0802
		Annual air passenger volume	+	0.0580	0.0288	0.0434
	Pressure	Annual air cargo volume	+	0.0305	0.0418	0.0362
		Hours of work per person in ground service	-	0.0136	0.0469	0.0303
		Labor cost ratio	-	0.0473	0.0593	0.0533
		Air-rail intermodal transport level	+	0.0306	0.0379	0.0342
		Average travel time of passengers	-	0.0215	0.0322	0.0269
	State	Fixed assets	+	0.0739	0.0378	0.0559
		Intangible assets	+	0.0418	0.0512	0.0465
		Number of self-service consignment devices	+	0.0466	0.0286	0.0376
		Number of self-service check-in devices	+	0.0180	0.0464	0.0322
		Free Wi-Fi coverage	+	0.0442	0.0375	0.0408
		Number of passenger service applets	+	0.0112	0.0254	0.0183
	Impact	Total airport revenue	+	0.0331	0.0304	0.0318
		Proportion of nonaviation revenue	+	0.0153	0.0579	0.0366
		Passenger satisfaction	+	0.0217	0.0454	0.0335
		Comprehensive environmental protection level	+	0.0100	0.0375	0.0237
	Response	Degree of propaganda of intelligence concept	+	0.0235	0.0284	0.0259
		Intangible assets and R&D investment	+	0.0334	0.0394	0.0364
		Degree of policy support	+	0.0516	0.0387	0.0452
		Fixed asset investment	+	0.0893	0.0828	0.0860

four first-tier cities—Shanghai, Guangzhou, Shenzhen, and Beijing—and one subprovincial coastal city, Xiamen, each of which is at the forefront of China's economic and population development and urban modernization. By 2020, the annual per capita GDP of each city where the five listed airports are located is higher than 120,000 RMB, and the proportion of tertiary industry is higher than 60%, with high quality of urban development. The five listed airports play a pivotal role in China's air transportation system, accounting for 19.06% of the country's total passenger volume and 53.35% of the country's total cargo volume in 2020. As the earliest listed international airports in China, each airport has implemented the concept of "smart airport" in terms of configuration and design, and there are a large number of self-service equipment in the airport, so passengers can enjoy self-service check-in, self-service baggage check-in, passenger service miniprogram, and other self-service processes. By evaluating the intelligence level of listed airports and diagnosing and analyzing its influencing factors, it is of great significance to provide reliable reference for the construction and transformation of future airport intelligence.

3.2. Airport Intelligence Level Evaluation

3.2.1. Determination of Weight Methods. Firstly, the AHP method is used to the advantages and disadvantages of each indicator in the system by two-by-two comparison between relevant indicators, and use the judgment results to comprehensively calculate the weights among the indicators. Then, the weights are determined according to the entropy weigh method based on how much information is available about the indicators, which objectively reflects the importance of the indicators in the evaluation [18]. In the evaluation index system of this paper, the AHP method and the entropy weight method are equally important, and the comprehensive weights are calculated by averaging and weighting in order to reflect the airport intelligence level more rigorously.

(1) AHP method

The main idea of AHP method [19] is to decompose the required objectives into multiple component factors according to the nature of the research object, to hierarchize them according to the interrelationship between the component factors to form a hierarchical structure model, and then analyze them by layer to finally obtain the importance weights of the highest layer. The basic process of AHP method is shown in Figure 2.

(2) Entropy weight method

The initial matrix for evaluation is specified as follows:

$$X = \begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1n} \\ x_{21} & x_{22} & \cdots & x_{2n} \\ \vdots & \vdots & & \vdots \\ x_{m1} & x_{m2} & \cdots & x_{mn} \end{bmatrix}. \quad (1)$$

x_{ij} is the data for indicator j for airport i.

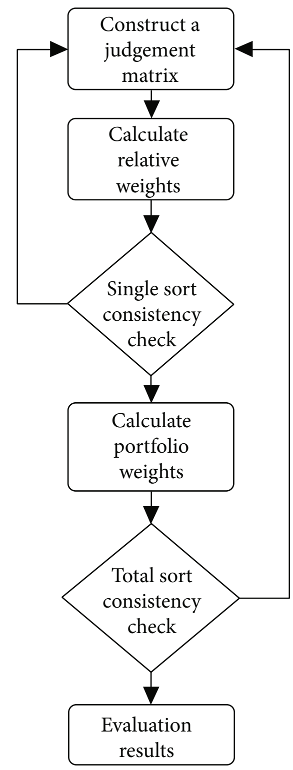

Figure 2: Basic process of AHP hierarchical analysis.

Standardization of raw data

$$\text{Positive indicators}: r_{ij}^{+} = \frac{x_{ij} - \min\{x_{ij}\}}{\max\{x_{ij}\} - \min\{x_{ij}\}},$$
$$\text{Negative indicators}: r_{ij}^{-} = \frac{\max\{x_{ij}\} - x_{ij}}{\max\{x_{ij}\} - \min\{x_{ij}\}}, \quad (2)$$

which gives the standardization matrix $R = \{r_{ij}\}_{mn}$, where r_{ij} is the standardized value of indicator j for airport i.

Calculating weights

$$y_{ij} = \frac{r_{ij}}{\sum_{i=1}^{m} r_{ij}},$$
$$e_j = -K \sum_{i=1}^{m} y_{ij} \ln y_{ij}, \quad (3)$$

where e_j is the information entropy, y_{ij} is the weight of airport i indicator j, K is a constant, $K = 1/\ln m$, and when $y_{ij} = 0$, set $\ln y_{ij} = 0$.

This leads to the definition of the weight entropy w_j as follows:

$$w_j = \frac{1 - e_j}{\sum_j 1 - e_j}, \quad (4)$$

where $w_j \in [0, 1]$ and $\sum_{j=1}^{m} w_j = 1$.

According to the equation w_j, the combined weight average W_j by the AHP hierarchical analysis and the entropy weight method can be obtained (as shown in Table 1 above).

3.2.2. Evaluation Method. Airport intelligence level evaluation belongs to the system engineering category. The TOPSIS model can be used to study the distance between the airport intelligence level and the ideal state. The model is an effective multi-indicator, multiprocessing decision analysis method, which is mainly ranked by detecting the distance between the evaluation object and the optimal solution and the worst solution, and if the evaluation object is closest to the optimal solution and far from the worst solution, it is the best, and vice versa is the worst [20]. The TOPSIS model has the advantages of easy calculation, small sample size requirement, and reasonable results. This paper improves the accuracy of the TOPSIS model by using a combination of subjective and objective approaches to determine the indicator weights and by building a decision matrix from the five subsystems of the DPSIR model.

(1) Construction of a weighted canonical matrix

$$C = \left(c_{ij}\right)_{m\times n} = W_j r_{ij} \tag{5}$$

(2) Calculate the positive ideal solution

$$C^{+} = \left\{\max_{i\in m} c_{ij}(j = 1, 2,\cdots,n)\right\} = \left\{c_1^{+}, c_2^{+},\cdots,c_m^{+}\right\} \tag{6}$$

Negative ideal solution

$$C^{-} = \left\{\min_{i\in m} c_{ij}(j = 1, 2,\cdots,n)\right\} = \left\{c_1^{-}, c_2^{-},\cdots,c_m^{-}\right\} \tag{7}$$

(3) Calculate the distance to the positive ideal solution

$$S_i^{+} = \sqrt{\sum_{j=1}^{n}\left(c_{ij} - C^{+}\right)^2 (i = 1, 2,\cdots,m)} \tag{8}$$

Distance to negative ideal solution

$$S_i^{-} = \sqrt{\sum_{j=1}^{n}\left(c_{ij} - C^{-}\right)^2 (i = 1, 2,\cdots,m)} \tag{9}$$

(4) Calculating the posting schedule

$$f_i = \frac{S_i^{-}}{\left(S_i^{-} + S_i^{+}\right)}, 0 \le f_i \le 1 \tag{10}$$

(5) The airport intelligence level is evaluated according to the value of f_i. The higher the value of f_i, the higher the airport rating, and the higher the airport intelligence level and vice versa (see Table 2).

3.2.3. Airport Intelligence Level Evaluation Results. According to the above research method, the comprehensive evaluation value of the intelligence level of five listed airports in China can be calculated (Table 3). The evaluation results are positively correlated with city and airport realities. Airports located in better economic regions with better facilities achieved higher rankings. According to the evaluation results, airport D has the highest intelligence level, with an overall score of over 0.64 and a high level (IV), followed by airport A and airports B and C, with an overall score of around 0.52 and a relatively high airport intelligence level (III), respectively, and airport C and airport E have an overall score of 0.3872 and 0.2731, with a general intelligence level (II). The intelligence level of each airport is most influenced by the development level of the city where it is located. Airports D and A with a high intelligence level are located in Beijing and Shanghai, respectively, where the city's economy, policies, and urban construction have experienced many years of development and precipitation, and the airport construction has developed steadily throughout the year. Similarly, Guangzhou and Shenzhen, where airports B and C are located, are located in the most economically developed Pearl River Delta region of China, with developed trade and thus airport development, but Shenzhen airport is slightly below the higher standard due to its development history and location overlap with Guangzhou. The airport E in Xiamen, on the other hand, is constrained by the city's economic, demographic, and policy factors and is in a more passive state, so the intelligence level is relatively low.

3.2.4. DPSIR Subsystem Evaluation Result Analysis. Base on the same methodology, the above results were further analyzed to calculate the subsystem evaluation values for each subsystem of the airport intelligence level subsystem (Table 4).

According to Table 5, the level of airport intelligence for each subsystem is analyzed as follows:

(1) *Driving Force Subsystem. Airport Intelligence Level Driving Force Subsystem Posting Progress Ranking and Comprehensive System Ranking Consistent.* On the one hand, the development of economic and social factors brings about the development of the overall intelligence level of the city and also brings about the continuous improvement of the passenger and cargo transportation volume of the airport. On the other hand, the high quality of the economic and social development promotes the coordinated development of the smart city and the smart airport.

Table 2: Airport intelligence level evaluation scale.

Intelligence level	Standard
Low (I)	$f_i \leq 0.2$
General (II)	$0.2 < f_i \leq 0.4$
Relatively high (III)	$0.4 < f_i \leq 0.6$
High (IV)	$0.6 < f_i \leq 0.8$
Very high (V)	$0.8 < f_i \leq 1$

Table 3: Results and values of S_i^+ and S_i^- for each airport's intelligence evaluation.

Airport	S_i^+	S_i^-	f_i	Rank
A	0.1220	0.1370	0.5289	2
B	0.1228	0.1340	0.5218	3
C	0.1539	0.0973	0.3872	4
D	0.0952	0.1800	0.6540	1
E	0.2033	0.0766	0.2737	5

Table 4: Evaluation results of each airport's intelligence level subsystem.

Airport	Driving force (D)	Pressure (P)	State (S)	Impact (I)	Response (R)
A	0.5658	0.4458	0.6498	0.6174	0.4159
B	0.5130	0.3804	0.7450	0.5792	0.1948
C	0.4300	0.4048	0.4258	0.3726	0.1896
D	0.6295	0.6236	0.6358	0.4792	0.3341
E	0.3131	0.3902	0.0416	0.4135	0

Table 5: Classification of subsystem coupling coordination and determination criteria for airport intelligence level.

Category	Standard
Low coordination (I)	$D \leq 0.3$
Medium coordination (II)	$0.3 < D \leq 0.5$
High coordination (III)	$0.5 < D \leq 0.8$
Extreme coordination (IV)	$0.8 < D \leq 1$

(2) *Pressure Subsystem*. The pressure subsystem posting progress of each airport intelligence level is around 0.4, which is at a high level, mainly because the busy degree of city and airport is negatively related to the pressure system posting progress. With the construction of smart airports in recent years, working hours of ground service staff and airport labor costs are being reduced. At the same time, a more complete air-rail network and smarter airports have led to a continuous reduction in passenger airport travel time, resulting in a higher level of stress subsystems.

(3) *State Subsystem*. All airports except airport E have an intelligence level state subsystem posting progress higher than 0.4, mainly because of the large gap in total fixed assets and intangible assets among airports, with airport E's fixed assets less than 1/6 of those of airports A, B, and D and intangible assets significantly lower than those of other airports. Therefore, more complete smart airport hardware and software facilities can effectively suppress the impact of stress systems on the airport intelligence level and increase the overall intelligence level posting progress.

(4) *Impact Subsystem*. There is no excessive polarization in the posting progress of each airport's intelligence level impact subsystem, and all airports are higher than 0.4 except for airport C, which is 0.3726. Mainly, the proportion of nonaviation revenue and the passenger satisfaction have a greater impact on the impact subsystem, and their combined weights reach 0.0366 and 0.0335, respectively. A healthy airport revenue structure characterizes a strong multifaceted airport development, which can enhance the travel experience of passengers at the airport and indicates that the airport needs to continuously improve its internal structure, including strengthening the development of smart facilities and commercial and humanistic features.

(5) *Response Subsystem*. All airports except airport A have a response subsystem posting rate below 0.4. The reason for this is that each airport is affected by the COVID-19 epidemic, both government subsidies and the airport's own investment and operations are hit to varying degrees in 2020, and the construction of airport E focuses on "humanistic airport," resulting in the overall low progress of response subsystem posting. The fixed asset investment accounts for the most in the response subsystem, which reaches 0.0860, indicating that airport infrastructure construction plays an important role in the airport intelligence level, which can effectively promote the rise of the response subsystem posting progress.

Collectively, it is possible to analyze the internal relationships between subsystems according to the DPSIR framework. Under the overall driving force of social development, the development of airport intelligence level is under a certain degree of pressure, leading to changes in the airport state, and the high-intensity driving force can improve the posting progress of the pressure and state subsystem. The impact subsystem is the feedback of each subsystem state change, and the response subsystem can regulate each subsystem state and play a role in improving the level of intelligence. The evaluation results are in line with the airport construction and socioeconomic development, and it can be observed that the overall progress of the posting of the response subsystem of each airport is the lowest, which indicates that the multifaceted investment in airport intelligence is the point that needs to be focused on improvement.

3.3. Subsystem Coupling Coordination Analysis

3.3.1. Coupling Coordination Model. Airport intelligence is a quantitative evaluation indicator that reflects the sustainability of the relationship between airport and city, as well as the interactive coupling between the "airport" as the foundation of the transportation system and the "passenger travel" as the carrier. By introducing the coupling degree (C^*), coordination degree (D), and coordination index T to establish the coupling model of the subsystems of the airport intelligence level, the coupling coordination degree between the subsystems of the airport intelligence level index is identified.

$$\begin{aligned} C^* &= \left\{ \frac{\prod_{i=1}^{n} u_i}{\left[\sum_{i=1}^{n} u_i/n\right]^n} \right\}^{1/n}, \\ T &= \alpha u_1 + \beta u_2 + \cdots + \omega u_n, \\ D &= \left(C^* \times T\right)^{1/n}. \end{aligned} \tag{11}$$

In the formula, u_i is the assessment value of the intelligence level of each subsystem; n is the number of subsystems; T is the coordination index between two of the five subsystems of DPSIR. So in the formula, $n = 2$. α, β, etc., are coefficients to be determined, here taken as 0.5.

The degree of coordination between two subsystems is divided into four levels: low coordination (I), medium coordination (II), high coordination (III), and extreme coordination (IV) (Table 5), where the closer the value to 1, the higher the degree of coordination.

3.3.2. Analysis of Measurement Results. Bringing the above results into equation (11), the intrinsic relationship between the subsystems around the DPSIR model framework can be obtained (Table 6). In terms of coupling degree, the coupling degree between two of each subsystem is greater than 0.91, which is at an extremely high level, indicating that each subsystem has a strong degree of influence on each other; in terms of coordination degree, all subsystems are in a high state of coordination between two of each other, indicating a high degree of benign coupling of each subsystem. Among the subsystems of airport intelligence, changes in one subsystem will largely affect the other subsystems and thus have an impact on the whole, and the high coordination degree indicates that the subsystems have a strong ability to promote each other at a high level.

3.4. Obstacle Degree Diagnosis of Airport Intelligence Level

3.4.1. Obstacle Model. At present, China's airports are in the transition period of intelligence development, and finding the weaknesses of smart airport development is an important means to enhance the airport intelligence level, by introducing an obstacle model to diagnose the obstacle factors for each subsystem and individual indicator of the airport intelligence level. Specifically, by introducing the indicator contribution degree G_{ij}, the indicator deviation degree I_{ij}, and the indicator obstacle degree N_{ij}, the calculation steps are as follows:

$$\begin{aligned} G_{ij} &= w_j z_j, \\ I_{ij} &= 1 - X_{ij}, \\ N_{ij} &= \frac{I_{ij} \times G_{ij}}{\sum_{j=1}^{24} \left(I_{ij} \times G_{ij}\right)}. \end{aligned} \tag{12}$$

In the formula, X_{ij} is the value of a single indicator after standardization, the value of G_{ij} is the combined weight of the jth indicator in the indicator layer after correction by the entropy weight method, and z_j is the weight accounted for by each subsystem.

3.4.2. Diagnosis of the Main Obstacles at the Indicator Level. According to Table 7, it can be seen that the main obstacles to the intelligence level at each airport are the driving force, state, response, and pressure subsystems. The proportion of nonaviation revenue, the average travel time of passengers, the regional fiscal revenue growth rate, the hours of work per person in ground service, the degree of policy support, the intangible assets, and R&D investment are also ranked high in several airports. This shows that the main obstacles to the level of airport intelligence are the proportion of nonaviation revenue, the average travel time of passengers, and the regional fiscal revenue growth rate. This also shows that the improvement of airport intelligence has a high demand for capital, airport revenue structure, airport equipment, and services, so in the future, airport construction needs to focus on improving the airport revenue structure and improving the efficiency of airport management and operation.

3.4.3. Subsystem Obstacle Degree Diagnosis. According to the analysis results of the obstacle degree of each index, the obstacle degree of each subsystem can be obtained, and the results are shown in Figure 3. As shown in Figure 3, from the system level, the pressure subsystem and impact subsystem barrier degree fluctuation are less in each airport, in the range of 0.5 to 1.5, which reflects the pressure subsystem and impact subsystem barrier degree of each airport is close. The same trend of changes in the state subsystem and the driving force subsystem confirms the intrinsic connection between the two subsystems and their important role in the system of airport intelligence level. From the airport level, the state subsystem is the primary obstacle for airport C and airport A, the pressure subsystem is the primary obstacle for airport A and airport D, the driving force subsystem is the primary obstacle for airport B, and the state and pressure subsystems have the highest frequency and are the main obstacles for airport intelligence level. In a comprehensive view, in the future development and construction of airport intelligence level, it is necessary to focus on improving the coordination and structural optimization of the development of the driving force, state, and response subsystems, to focus on regulating the pressure subsystem. Meanwhile, it is necessary to take into account the continuous improvement of the impact subsystem in order to improve the airport intelligence level.

Table 6: Airport intelligence level subsystem coupling coordination degree.

Coupling coordination	Driving force * pressure	Pressure * state	State *impact	Impact * response	Response * driving force	Response * pressure	Response * state
Coupling degree	0.9991	0.9994	0.9999	0.9307	0.9313	0.9166	0.9281
Coordination	0.7148	0.7182	0.7041	0.5790	0.5785	0.5906	0.5812
Degree of coordination	Highly coordinated	Highly coordinated	Highly coordinated	Highly coordinated	Highly coordinated	Highly coordinated	Highly coordinated

Table 7: Ranking of the main obstacles to the airport intelligence level.

Airport	Item	Indicators and ranking 1	2	3	4	5
A	Obstacles	Free Wi-Fi coverage	Comprehensive environmental protection level	Average travel time of passengers	Regional fiscal revenue growth rate	Proportion of tertiary industry
	Degree%	30	30	29.41	28.37	25.85
B	Obstacles	Hours of work per person in ground service	Proportion of nonaviation revenue	GDP per capita	Air-rail intermodal transport level	Fixed asset investment
	Degree %	37.5	36.99	35.02	25	23.67
C	Obstacles	Proportion of nonaviation revenue	Degree of policy support	Fixed assets	Number of self-service consignment devices	Intangible assets and R&D investment
	Degree %	38.16	38.10	34.72	33.96	31.78
D	Obstacles	Average travel time of passengers	Intangible assets	Regional fiscal revenue growth rate	Passenger satisfaction	Hours of work per person in ground service
	Degree %	47.06	37.86	31.91	30	25
E	Obstacles	Number of passenger service applets	Number of permanent residents	Intangible assets and R&D investment	Annual air passenger volume	Degree of policy support
	Degree %	100	54.45	52.94	48.79	47.62

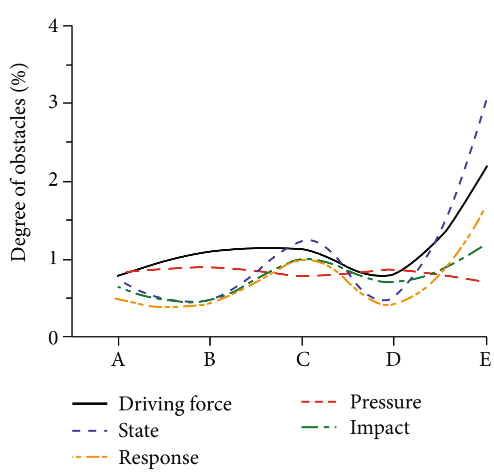

Figure 3: Obstacles of each subsystem of airport intelligence level.

4. Conclusions and Discussion

4.1. Conclusion. This paper takes five listed airports in China as the research object, and based on the DPSIR model, 24 indicators are selected to build an airport intelligence level evaluation index system, to evaluate the airport intelligence level of five airports in 2020, and to analyze and summarize their influence factors.

(1) The five listed airports in China are divided into three levels of intelligence, with airport D having the highest level of intelligence with a high rating, recorded as IV; followed by airport A and airport B with a relatively high intelligence level recorded as III; and lastly airport C and airport E with a general level of intelligence, recorded as II

(2) In terms of subsystem posting progress, the response subsystem posting progress is at a low value overall, while the rest of the subsystem posting progress is relatively close to each other overall. The pairwise coupling degree of each subsystem is higher than 0.91, which is a benign coupling

(3) From the viewpoint of obstacles, the main obstacle to the level of airport intelligence is the state subsystem, followed by the pressure, driving force, response, and impact subsystems. The main obstacles of each subsystem can be refined as the proportion of

nonaviation revenue, the average travel time of passengers, and the regional fiscal revenue growth rate

4.2. Discussion. Based on the above, in order to build an airport with a high level of intelligence in the future, the operational structure optimization, infrastructure construction, and policy response should be improved.

(1) Strengthen the economic policy response of airport construction and improve the performance of airport construction. Investment and construction of smart airports are subject to high socioeconomic constraints. Therefore, the government should give full play to its functions, which can realize the coordinated development of smart airport and economic development by increasing investment funds for smart airport construction as well as optimizing the management system

(2) Promote the optimization of airport operation structure and highlight the all-round development of intelligent airport services. Balanced development of multiple industries within the airport enhances the level of passenger service experience, fully utilizes the airport's important role in the transportation system, drives airport revenue growth, and forms an all-round, high intelligence level service industry chain

(3) Promote the construction of hard and software facilities of smart airport to realize the improvement of airport intelligence level. The quantity and quality of the construction of intelligent facilities are important obstacle factors for the airport intelligence level. To enhance the level of airport intelligence, airports and government must ensure a high level of construction of hard and software facilities and improve the popularity of various self-service device, intelligent security checks, and various cell phone software for passenger services

In this paper, the TOPSIS method combining AHP method and entropy weight method is used to evaluate the of airport intelligence level, which improves the credibility of the evaluation results, but due to the extremely low availability of some airport data, there is still room for improvement in terms of the index system reflecting smart airport facilities and smart services. Meanwhile, in terms of research content, exploring the evolution of the intelligence level of more airports in the time dimension is also one of the feasible research directions for the future.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare that there is no conflict of interest regarding the publication of this article.

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