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Research Article

Design of Air Passenger Travel Choice Intention Prediction System Based on Deep Learning

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Under the Beijing-Tianjin regional comprehensive transportation system, the flow of air passengers between multiple airports in the region is more frequent. The fundamental reason for the flow of air passengers is that there are differences in the level of service quality provided by airports and airlines in the region. Passengers' choice intention is the consumption and purchase decision of passengers on aviation services. By constructing a Logit model, this paper analyzes the degree of influence on the travel choice intention of air passengers in the Beijing-Tianjin region from five aspects: individual passenger demographic characteristics, travel purpose, ground transportation characteristics, airport operation capacity, and airport soft power. Passengers can effectively predict the choice of air travel mode in the Beijing-Tianjin region. The results show that Beijing Capital Airport is favored by business travelers; Beijing Daxing International Airport is favored by travelers because of its fast security check-through speed; for Tianjin Binhai International Airport, the convenience of getting in and out of the airport by car and the speed of airport security check-through are two significant factors. Indicators do not affect the selection of airports; reasonable follow-up arrangements when airport flights are delayed are the only significant but negatively correlated factor; the research design results provide new ideas for the analysis of passenger travel mode selection behavior in multiple airport areas, enriching the data-driven research on transportation choices.

1. Related Introduction

Since the birth of the basic theory of artificial intelligence, artificial intelligence technology and applications have developed rapidly, and machine learning is an important form of artificial intelligence. Machine learning has experienced two waves from shallow machine learning to deep learning. With the continuous development of machine theory and applications, various shallow machine learning models have been proposed one after another. Typical machine learning models include support vector machines invented by Cortes and others. At present, the main methods for airport passenger throughput include two aspects, linear prediction and nonlinear prediction. Linear-based methods include time series models, grey models. Although these methods have achieved good prediction results, they cannot reflect nonlinear trends, and the prediction accuracy needs to be improved; nonlinear-based methods include BP neural network, recurrent neural network, long short-term memory network, support vector regression, and other models; in addition, the combined model also achieved good prediction results. This type of model can fit the nonlinear relationship between input and output and has strong fault tolerance. It is also a commonly used research model for airport passenger throughput forecasting. In a word, machine learning has become one of the key research areas of artificial intelligence at present, and it is applied in many fields, including speech processing, computer vision, and natural language processing. Machine learning has also achieved good results in regression prediction. In recent years, domestic and foreign scholars have achieved certain results in the research on the travel choice intention of air passengers. Different from previous studies, this paper not only focuses on the travel choice intention of air passengers but also can more intuitively reflect the travel choice intention of air passengers after calculation based on the consumption and purchase decision-making of air services by passengers. This paper belongs to a research proposition that considers comprehensive influencing factors. It does not just focus on the travel choice intention of air passengers but also studies the choice intention of passengers through the consumption and purchasing power of air services from the side. The model selected is mainly based on the Logit model. Finally, the feasibility and effectiveness of the model are verified [1–9].

2. Related Theoretical Methods

A deep neural network model framework is built, as shown in Figure 1. First, the transmission parameters of the data are explained, including time step, which indicates how many historical input values are used to predict future values; learning rate, which indicates the learning step size in gradient descent; input dimension, output dimension; batch size; batch number; hidden the number of neurons in the layer, the number of neurons in the GRU layer, and the number of GRU layers. The data are divided into batches before entering the neural network, and each batch is divided into time steps. The data first pass through the FIR filter layer, then enter the input layer, then pass through the hidden layer, then pass through several GRU layers for time series prediction, finally pass through the hidden layer and the output layer to output data, and train the parameters of each part of the network by comparing with the label data and BPTT propagation. During the training process, if the setting of the learning rate is too large, the loss value will oscillate around the local optimal solution. If the setting of the learning rate is too small, the convergence will be slow in the gradient descent process [10–14].

3. Model and Variable Selection

3.1. Model Selection. For the airport selection research of passenger travel, the deep neural network model and the Logit model are the most commonly used methods. The Logit model is the earliest discrete choice model, and it has gradually formed a complete discrete choice model system, such as the probit model, the NL model, and the mixed Logit model.

In this paper, the standard polynomial Logit model is used to study the probability of airport selection for Beijing-Tianjin air passengers. The theoretical basis of the standard polynomial Logit model is the stochastic utility theory and the utility maximization hypothesis. Therefore, the effect function 1.1 is introduced first [15–19].

$$T_{ki} = x_k\beta_i + \varepsilon_{ki}. \tag{1}$$

Among them, T_{ki} is the utility of individual k choosing i scheme (such as choosing Beijing Daxing International Airport), x_k is the set of influencing factors, such as gender, and age, β_i is the generation of influencing factors in choosing the i-th scheme. The estimated parameter vector, ε_{ki}, is the error term.

When $T_{ki} > T_{kj}$ ($i \neq j$, $i, j \in J$, J represents the set of airports that can be selected), the individual will choose the scheme i. Therefore, the probability formula for individual k to choose plan i is 1.2.

$$P_k(i) = P\left(T_{ki} > T_{kj}\right), \quad (i \neq j). \tag{2}$$

Substituting formulas (1) into (2), and assuming that ε_{ki} obeys the generalized extreme value distribution, formula (3) of the standard polynomial Logit model can be derived, that is, the probability that individual k chooses the i airport. The standard polynomial Logit model needs to assume that one item is selected as the benchmark group (this paper takes Beijing Capital International Airport as the benchmark group). The standard polynomial Logit model is not only fast and stable but also has the assumption that each airport in Beijing and Tianjin is independent and irrelevant, which is conducive to the analysis of each indicator [20].

$$P_{ki} = \frac{e^{\beta x_{ki}}}{\sum_{j\in J}^{J} e^{\beta x_{kj}}}. \tag{3}$$

In expression (3), P_{ki} represents the probability of choosing an airport i for air passenger k; β_x represents the deterministic utility generated when choosing an airport for air passenger travel and using the influencing factors that air passengers experience when choosing an airport. The linear combination of $i, j \in J$, J represents the set of airports that can be selected.

In this paper, Logit regression is performed on each influencing factor through Stata software to explore the significant degree of influence of each factor on the choice of each airport. Then, the multinomial Logit model is solved to obtain the selection probability of each individual for each airport, and then, the selected probability of each airport is summed and averaged to finally obtain the passenger occurrence probability of each airport.

3.2. Data Acquisition and Analysis. This paper extracts the demographic characteristics, travel purpose, ground transportation characteristics, airport operation capacity, airport soft power, and other factors that may affect the passenger's choice behavior at the individual level of passengers and establishes a quantitative analysis model to describe the passenger's choice behavior, as shown in Table 1. By exploring the effect on choice behavior, the selected elements and dimensions contain the relevant intentions at the individual level of air tourist travel.

3.2.1. Demographic Characteristics. Based on network data and past research, it is found that women's travel frequency is generally higher than that of men for shopping, leisure, entertainment, and other reasons, and the travel frequency of young people is generally higher than that of middle-aged and elderly people. It can be seen that demographic characteristics have a certain degree of influence on passengers' travel choices. However, due to the protection of the

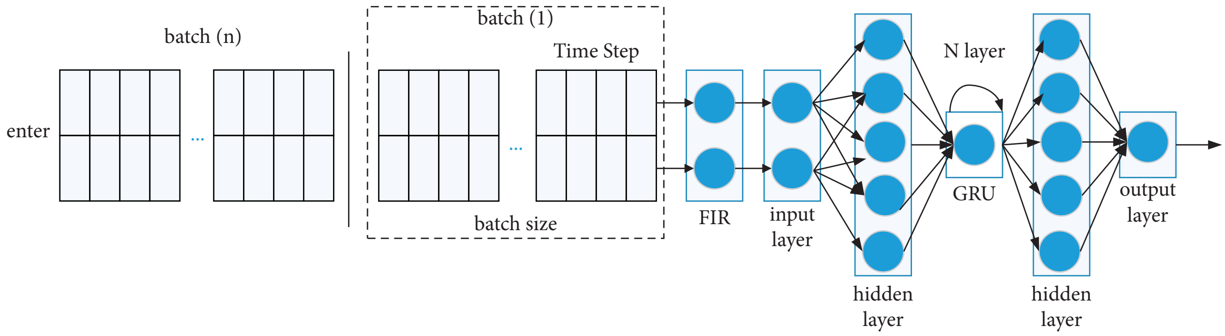

Figure 1: Deep neural network model framework.

Table 1: Variable names, categories, attributes, and definitions.

Variable	Variable category	Variable properties	Definition
Gender	Demographic characteristics	Numeric variables	Dependent variable takes a value of 1 if the gender is male; otherwise, it is 0
Age		Categorical variables	18–29 years old, take the value 1; 30–39 years old, take the value 2; 40–49 years old, take the value 3; 50–59 years old, take the value 4; Over 60 years old, take the value 5
Whether or not to travel for leisure tourism		Numeric variables	For the dependent variable, if the passenger travels for leisure tourism, the value is 1; otherwise, 0
Whether the purpose of travel is to visit relatives and friends	Purpose of travel	Numeric variables	For the passenger's travel purpose of visiting relatives and friends, the value is 1; otherwise, 0
Whether you are traveling for business purposes		Numeric variables	For the passenger, if the passenger travels for business purposes, the value is 1; otherwise, 0
Access to the airport is quick and easy to get in and out of the airport	Ground transportation features	Categorical variables	Great influence, take the value 1; larger influence, take the value 2; general influence, take the value 3; slightly affect, take the value 4; no effect, take the value 5
The airport parking facilities are well built		Categorical variables	Great influence, take the value 1; larger influence, take the value 2; general influence, take the value 3; slightly affect, take the value 4; no effect, take the value 5
Check-in at the airport is easy and fast	Airport operational capacity	Categorical variables	Great influence, take the value 1; larger influence, take the value 2; general influence, take the value 3; slightly affect, take the value 4; no effect, take the value 5
The airport has a high punctuality rate of flights		Categorical variables	Great influence, take the value 1; larger influence, take the value 2; general influence, take the value 3; slightly affect, take the value 4; no effect, take the value 5
Reasonable follow-up arrangements in the event of flight delays at the airport		Categorical variables	Great influence, take the value 1; larger influence, take the value 2; general influence, take the value 3; slightly affect, take the value 4; no effect, take the value 5
Airport security passes quickly		Categorical variables	Great influence, take the value 1; larger influence, take the value 2; general influence, take the value 3; slightly affect, take the value 4; no effect, take the value 5
The airport terminal environment is clean	Airport soft power	Categorical variables	Great influence, take the value 1; larger influence, take the value 2; general influence, take the value 3; slightly affect, take the value 4; no effect, take the value 5
There are many airport-related supporting entertainment facilities		Categorical variables	Great influence, take the value 1; larger influence, take the value 2; general influence, take the value 3; slightly affect, take the value 4; no effect, take the value 5
The airport flight information is prominently located and the information is correct		Categorical variables	Great influence, take the value 1; larger influence, take the value 2; general influence, take the value 3; slightly affect, take the value 4; no effect, take the value 5

individual privacy of respondents, complete demographic characteristics cannot be obtained. Therefore, extracting characteristics such as gender and age helps to explore the demographic characteristics in the Beijing-Tianjin area.

3.2.2. Purpose of Travel. Combined with the economic and social construction conditions in the Beijing-Tianjin region, the purpose of travel also has an impact on travelers' travel choices. Therefore, the vast majority of tourists choose

Beijing's two airports for business and leisure purposes. Therefore, in this paper, the purpose of travel is divided into three categories: leisure travel, visiting relatives and friends, and business office, to help explore the impact of travel purpose in the Beijing-Tianjin region on the travel choice of air passengers [21].

3.2.3. Characteristics of Ground Traffic. With the development of social construction planning, the availability of ground transportation tends to be average, and airport options are basically available. Therefore, this paper focuses on the impact of ground transportation convenience on travelers' travel choices. The convenience of entering and leaving the airport by car and the construction of airport parking lot facilities are used as two indicators to reflect the convenience of ground transportation.

3.2.4. Airport Operation Capability. The impact indicators of airport operation capacity on passengers' choice of an airport are mainly reflected in the convenience of airport procedures, the on-time rate of airport flights, the rationality of airport follow-up arrangements when flights are delayed, and the rate of airport security checks. Excellent airport operation ability can strongly attract passengers to choose. Therefore, this paper incorporates various indicators of airport operation ability into the exploration factors to explore the impact of airport operation ability on air passengers' travel choices in the Beijing-Tianjin region.

3.2.5. Airport Soft Power. Under the condition that the hard demands are basically satisfied, the soft power of the airport is the characteristic competitiveness of the airport, which can improve the passenger stickiness, enhance the travel experience of passengers, and increase the loyalty and frequency of choice. This research uses the airport environment, the number of airport supporting entertainment facilities, and the accuracy and convenience of airport flight information transmission as indicators of airport soft power to explore the impact of airport soft power on air passengers' travel choices in the Beijing-Tianjin region [22, 23].

4. Empirical Analysis

Based on the Beijing-Tianjin regional air passenger travel choice data obtained from the questionnaire, the relevant data sources are mainly obtained through random interviews in the form of Richter scales, and Stata16.0 was used to carry out descriptive statistics, linear relationship analysis, and multiple Logit model solutions for variables. In order to make the running results clearer and more beautiful, this paper encodes the variables in the form of pinyin: gender (xb), age (nl), whether the travel purpose is for leisure travel (xxly), whether the travel purpose is to visit relatives and friends (tqfy), whether the purpose of travel is for business office (swbg), the airport is convenient and fast to travel by car (ccbj), the airport parking lot facilities are well constructed (tcch), the airport check-in procedures are convenient and fast (sxbj), and the airport flight has a high punctuality rate (zdl), reasonable follow-up arrangements when airport flights are delayed (aphl), fast airport security check (ajk), clean and tidy airport terminal environment (hj), more airport-related entertainment facilities (ylss), airport flight information is eye-catching. The information is correct (xxzq). The selection of relevant variables is mainly based on the most common variables of air travel.

4.1. Running Results. In order to better observe the variables, this study carried out descriptive statistics and linear relationship analysis on the variables. The descriptive statistics of the variables are shown in Table 2, where the first column obs represents the observed quantity, the second column mean represents the mean, the third column Std.Dev. represents the standard deviation, the fourth column Min represents the minimum value, and the fifth column Max represents the maximum value.

In order to reduce the deviation of the influence of the respective variables on the dependent variable, this paper also explores whether there is a linear relationship between the respective variables and uses Stata16.0 to test the linear relationship between the variables, as shown in Table 3. It can be found that the VIF values of the respective variables are all less than 3, indicating that there is no significant linear relationship between the respective variables, which proves that the subsequent Logit model regression solution value deviation is small, and the results are efficient.

In this paper, the multinomial Logit model is solved, and the choice of airport for air passenger travel is taken as the dependent variable (select Beijing Capital International Airport, value 1; Beijing Daxing International Airport, value 2; Tianjin Binhai International Airport, value 3), and various indicators of factors such as demographic characteristics, travel purpose, ground traffic characteristics, airport operating capacity, and airport soft power are used as independent variables, and Stata software is used to solve the model to obtain the degree of influence of each factor on each choice, as shown in Tables 4-6.

4.2. Analysis of Results. It can be seen from the results in Tables 4-6. The first column in Table 4 to Table 6 is each factor variable; the second column is the coefficient corresponding to each variable; the positive or negative of the coefficient is logically related to the correlation of each factor, and a positive number indicates a positive correlation; otherwise, it is A negative correlation; the importance of each factor can be obtained by the absolute value of the coefficient; the third column is the standard error of each factor; the degree of dispersion of the sample can be judged by its size; the fourth column is the corresponding value of each variable Z values; the fifth column is the standard error for each factor. This column is the P value corresponding to each variable. Usually, these two values are used to judge the significance of each variable. Under the 90% confidence level, if the absolute value of z is greater than 1.645 and the P-value is less than 0.10, then the variable is selected by passengers.

Table 2: Descriptive statistics for variables.

Variable	Observational measurement	Average value	Standard error	Minimum	Maximum
Gender (xb).	855	0.3883041	0.4876496	0	1
Age (nl).	855	1.762573	0.913599	1	5
Whether to travel for leisure tourism (xxly).	855	0.6584795	0.4744972	0	1
Whether to visit relatives and friends for the purpose of travel (tqfy).	855	0.0467836	0.2112987	0	1
Whether it is for business office purposes (swbg).	855	0.1918129	0.3939571	0	1
Airport selection	855	1.906433	1.496489	1	9
Easy and quick access to the airport (ccbj).	855	2.466667	1.328308	1	5
The airport parking facilities are well built (tcch).	855	3.274854	1.265841	1	5
Check-in at the airport is quick and easy (sxbj).	855	2.378947	1.352083	1	5
Airport flights have a high punctuality rate (zdl).	855	2.100585	1.328551	1	5
Reasonable follow-up arrangements in the event of airport flight delays (aphl).	855	2.269006	1.342918	1	5
Airport security passes quickly (ajk).	855	2.582456	1.2976	1	5
The airport terminal is clean and tidy (hj).	855	2.823392	1.253721	1	5
There are many airport-related supporting facilities (ylss).	855	3.633918	1.212936	1	5
The airport flight information is prominently located and the information is correct (xxzq).	855	2.511111	1.299272	1	5

Table 3: Variable linear relationship test.

Variable	Bright	1/VIF
Whether the purpose of travel is to visit relatives and friends (tqfy).	2.80	0.357124
Whether it is for business office purposes (swbg).	2.67	0.374038
Airport selection	2.48	0.403751
Easy and quick access to the airport (ccbj).	2.44	0.410381
The airport parking facilities are well built (tcch).	2.33	0.429666
Check-in at the airport is quick and easy (sxbj).	2.26	0.442728
Airport flights have a high punctuality rate (zdl).	2.16	0.463237
Reasonable follow-up arrangements in the event of airport flight delays (aphl).	2.15	0.464106
Airport security passes quickly (ajk).	2.00	0.500020
The airport terminal is clean and tidy (hj).	1.62	0.617394
There are many airport-related supporting facilities (ylss).	1.41	0.711014
The airport flight information is prominently located and the information is correct (xxzq).	1.28	0.779130
Whether the purpose of travel is to visit relatives and friends (tqfy).	1.10	0.911822
Whether it is for business office purposes (swbg).	1.09	0.916891
Mean VIF	1.98	

Table 4: Logit model regression results for selecting Beijing Capital International Airport.

Choice 1 Variable	Quasi $R2 = 0.0266$			
	Regression coefficients	Standard error	With	p
Gender (xb).	−.2165614	0.1562371	−1.39	0.166
Age (nl).	0.0859551	0.0847011	1.01	0.310
Whether to travel for leisure tourism (xxly).	0.0969474	0.2420128	0.40	0.689
Whether the purpose of travel is to visit relatives and friends (tqfy).	0.1350224	0.3990109	0.34	0.735
Whether it is for business office purposes (swbg).	0.8002119	0.2929658	2.73	0.006
Easy and quick access to the airport (ccbj).	0.1194681	0.0838746	1.42	0.154
The airport parking facilities are well built (tcch).	−0.0071703	0.0733454	−0.10	0.922
Check-in at the airport is quick and easy (sxbj).	0.0790751	0.0912878	0.87	0.386
Airport flights have a high punctuality rate (zdl).	−0.0826886	0.0863616	−0.96	0.338
Reasonable follow-up arrangements in the event of airport flight delays (aphl).	0.1619173	0.0805046	2.01	0.044
Airport security passes quickly (ajk).	−0.2033971	0.0831281	−2.45	0.014
The airport terminal is clean and tidy (hj).	−0.0440311	0.082426	−0.53	0.593
There are many airport-related supporting facilities (ylss).	0.0193179	0.0682984	0.28	0.777
The airport flight information is prominently located and the information is correct (xxzq).	−0.0848699	0.0855178	−0.99	0.321

Table 5: Logit model regression results for selecting Beijing Daxing International Airport.

Choice 2	Quasi $R2 = 0.00775$			
	Regression coefficients	Standard error	With	p
Gender (xb).	0.0422496	0.3583026	0.12	0.906
Age (nl).	−0.6052624	0.2657307	−2.28	0.023
Whether to travel for leisure tourism (xxly).	−0.1346333	0.495872	−0.27	0.786
Whether the purpose of travel is to visit relatives and friends (tqfy).	0.0549319	0.7601636	0.07	0.942
Whether it is for business office purposes (swbg).	0.0565374	0.586965	0.10	0.923
Easy and quick access to the airport (ccbj).	−0.1697648	0.1847487	−0.92	0.358
The airport parking facilities are well built (tcch).	0.097763	0.1638026	0.60	0.551
Check-in at the airport is quick and easy (sxbj).	−0.0899377	0.2017813	−0.45	0.656
Airport flights have a high punctuality rate (zdl).	0.1975662	0.1815875	1.09	0.277
Reasonable follow-up arrangements in the event of airport flight delays (aphl).	−0.0473564	0.1714052	−0.28	0.782
Airport security passes quickly (ajk).	0.5481134	0.184276	2.97	0.003
The airport terminal is clean and tidy (hj).	−0.2903814	0.1798466	−1.61	0.106
There are many airport-related supporting facilities (ylss).	0.1305016	0.1604658	0.81	0.416
The airport flight information is prominently located and the information is correct (xxzq).	−20.772141	0.1917859	−1.00	0.320

Table 6: Logit model regression results for selecting Tianjin Binhai International Airport.

Choice 3	Quasi $R2 = 0.0255$			
	Regression coefficients	Standard error	With	p
Gender (xb).	0.0496101	0.1994063	0.25	0.804
Age (nl).	−0.0250308	−0.1079822	−0.23	0.817
Whether to travel for leisure tourism (xxly).	0.1335351	0.3157477	0.42	0.672
Whether the purpose of travel is to visit relatives and friends (tqfy).	0.5174501	0.4818168	1.07	0.283
Whether it is for business office purposes(swbg).	−0.4837559	0.3899762	−1.24	0.215
Easy and quick access to the airport (ccbj).	−0.2100871	0.107067	−1.96	0.050
The airport parking facilities are well built (tcch).	0.0822015	0.0915746	0.90	0.369
Check-in at the airport is quick and easy (sxbj).	0.020125	0.1152669	0.17	0.861
Airport flights have a high punctuality rate (zdl).	0.0813616	0.1112021	0.73	0.464
Reasonable follow-up arrangements in the event of airport flight delays (aphl).	−0.1190637	0.1030323	−1.16	0.248
Airport security passes quickly (ajk).	−0.2009067	0.1059133	−1.90	0.058
The airport terminal is clean and tidy (hj).	0.0614114	0.104984	0.58	0.559
There are many airport-related supporting facilities (ylss).	−0.0119767	0.0845989	−0.14	0.887
The airport flight information is prominently located and the information is correct (xxzq).	0.1267582	0.1076092	1.18	0.239

4.2.1. Beijing Capital International Airport. As shown in Table 4, the Z-values of the three indicators are more than 1.645, and the P-values are all less than 0.10, indicating that these three indicators are important for the influence of Beijing-Tianjin Airlines passengers, and choosing Beijing Capital International Airport is significant. From the perspective of travel purpose, it can be seen that most of the passengers who choose Beijing Capital International Airport are for business and office travel purposes. From the perspective of airport operation capability, Beijing-Tianjin Airlines passengers pay great attention to the rationality of the follow-up arrangements for flight delays at Beijing Capital International Airport and the speed of security inspection. These two items will directly affect whether Beijing-Tianjin Airlines passengers choose Beijing Capital International Airport.

4.2.2. Beijing Daxing International Airport. As shown in Table 5, the absolute values of the Z-values of the two indicators of age and the speed of passing through the airport security check are both greater than 1.645, and the P-values are both less than 0.10, indicating that these two indicators have a high level of significance. However, the corresponding coefficient of age is −0.605, indicating that age is negatively correlated with the choice of Beijing Daxing International Airport by air passengers, which reflects that age has no profound influence on the choice of Beijing Daxing International Airport. In terms of airport operation capability, only the speed of passing the airport security check has a significant impact, which reflects the degree to which the speed of passing the airport security check has an impact on the travel choices of Beijing-Tianjin air passengers.

4.2.3. Tianjin Binhai International Airport. According to Table 6, the absolute value of the Z value of the two indicators of the convenience and speed of entering and leaving the airport and the speed of airport security inspection is greater than 1.645, and the P-value is less than 0.10, indicating that the two indicators have a high level of significance. The coefficient corresponding to the convenience of entering and leaving the airport by car is −0.210, and the corresponding coefficient of the airport security check passing speed is −0.200, both of which are negative numbers, indicating that these two indicators have a negative correlation with the selection of Tianjin Binhai International Airport. Tianjin Airlines passengers have little influence on the choice of Tianjin Binhai International Airport.

5. Conclusion

According to the analysis of the results in chapter 4.2, it can be seen that the most important factor when choosing an airport is the airport's operational capability, especially the speed of passing through the airport security check. Efficiency needs. Therefore, the following conclusions can be drawn: (1) The airport is appropriately expanded, and the security check channel is increased. (2) Artificial intelligence to speed up the identification of dangerous goods is introduced, and the quality and efficiency of security inspections are improved. (3) Green passages are built to allow passengers without security inspection requirements to pass quickly. In this way, the travel time cost of Beijing-Tianjin Airlines passengers can be reduced, and the travel efficiency of passengers can be improved. According to the results of the model solution, it can also be concluded that the current regional airports with less passenger distribution have less influencing factors than the current Beijing-Tianjin hub airports, which indicates that if the regional airports want to attract more. There are many Beijing-Tianjin Airlines passengers while enhancing the airport's operational strength, and they need to focus on the corresponding soft power and combine regional characteristics and passenger characteristics to implement special services to increase the travel experience of passengers, so as to improve the Beijing-Tianjin Airlines passengers' interest in the airport. As for Beijing Capital International Airport, which is currently saturated with passengers, the first thing to consider is the passenger diversion strategy, and it will be completed jointly with Beijing Daxing International Airport and other airports in the two places. This requires the government to strengthen the air space between Beijing and Tianjin. The railway combined transport mode makes the transportation between the three places more accessible and convenient, reduces the gap between regions, and eliminates the inertial thinking of Beijing-Tianjin air passengers on previous travel choices, so as to make the allocation of air passengers between Beijing and Tianjin more convenient and reasonably average.

Data Availability

The dataset can be accessed upon request.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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