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A passenger risk assessment method based on 5G-IoT

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Abstract

For the airports worldwide, it is important to establish a "passenger integrity system" based on the basic information of passengers and their related credit system. Correspondingly, this paper develops a new risk assessment model for the passenger graded security check by introducing several new technologies to obtain the passengers' real-time status information as well as historical data. We first propose to deploy a variety of 5G-IoT devices to monitor the passengers in real time, including high-definition cameras, millimeter-wave security detectors, etc. We then rely on machine learning to analyze the passenger risk level and integrate improved analytic hierarchy process (AHP) with group decision theory, namely GD-AHP. According to the risk level, the passengers can be classified into known, ordinary and dangerous targets. The differentiated handling of different targets could significantly save the time of security check and improve the passenger experience.

Keywords: Risk assessment, 5G-IoT, Machine learning, Graded security check, Analytic hierarchy process (AHP), Group decision

1 Introduction

The airports around the world have been enthusiastic to improve security efficiency by applying new security technologies [1]. Iris, facial and fingerprint identification are in use at some airports of the USA to improve security efficiency. In November 2016, Chicago's O'Hare Airport opened two automatic security channels, which use advanced equipment such as millimeter-wave security detector to realize the transformation of many functions from manual operation to automated operation and reduce the security check time by about 30% while improve the security check effect [2]. Smart Lane, an intelligent security channel used in the UK airports, has realized automatic tray return mode and remote image interpretation, which greatly saves labor costs and improves security efficiency [3]. Shenzhen Airport adopts the "passenger differential security check mode," when the gate system at the security check site collects all kinds of key personnel information from the cloud platform of civil aviation public security information. After systematic evaluation, passengers are classified and treated with different levels of check standards according to their types, effectively improving the efficiency of security check [4].

The fifth generation (5G) mobile network is the latest breakthrough to meet the demands of modern society for high-speed wireless networks [5–7]. The performance goals of 5G are high data rate, reduced latency, energy saving, cost reduction, system capacity increase and large-scale equipment connection. Some technologies for 5G have emerged at the moment, such as millimeter-wave, large-scale multi-input multi-output and small cellular communication. The IoT consists of a network of physical devices connected with remote computational capabilities. IoT deals with low power devices which interact with each other through the Internet. The IoT services will provide technical support in areas such as smart cities, smart grids and smart homes, thereby increasing productivity, reducing costs and significantly improving people's daily lives.

The development and applications of 5G and Internet of things (IoT) have provided technical support for the intelligent construction of airport security, which is also the focus of this paper. At present, most airports upgrade their security system with new technologies such as millimeter-wave security detector, biometric identification or passenger risk assessment based on large data of civil aviation passengers. However, these technologies are usually used in isolation without effective combination. This paper proposes a new mode of airport graded security check, which combines a variety of new security technologies with large data of civil aviation passengers, carries out comprehensive risk assessment of passengers. In the passenger information collection stage, the IoT terminals are used to obtain the real-time passenger data, mainly including the high-precision surveillance cameras and millimeter-wave security detectors. In addition, these equipments are connected with the 5G wireless interfaces to achieve high speed and low latency transmission.

When it comes to security and risk assessment, the following research findings should be highlighted. Reference [8] introduced a formal threat screening game (TSG) model. The Security Risk Assessment Handbook [9], as well as the ISO 31000-2018 [10], supplies wide-ranging coverage that includes security risk analysis, mitigation and risk assessment reporting and provides the tools needed to solicit and review the scope and rigor of risk assessment proposals with competence and confidence. And the AHP method mentioned in our paper is one of the classical risk assessment algorithms. Reference [11] evaluates, for the US case, the costs and benefits of three security measures designed to reduce the likelihood of a direct replication of the 9/11 terrorist attacks and discusses the balance between economic input and the effectiveness of security measures, which has some inspiration for our research.

Passenger risk assessment is a complex decision-making process and serves as the premise of graded security check. However, due to the subjectivity of qualitative evaluation, the limitations of some statistical methods and the interference of many external factors which cannot be quantitatively described, passenger risk assessment has great ambiguity and uncertainty [12]. AHP has been widely used in the establishment of risk assessment model and the determination of index weight because of its concise and intuitive principle and wide practicability. The traditional AHP method uses 1–9 scale to obtain the judgment matrix and then calculates the weight. Although concise, it has strong subjectivity and is prone to problems such as the inverse order of thinking results and the disjunction of consistency between thinking and judgment matrix [13, 14]. For this reason, many scholars have improved the AHP method and put forward

many scaling systems [15–18]. Lv [19] made a systematic comparative analysis of various scales and concluded that the index scales could solve the problem of the disconnection between the judgment matrix and the consistency of thinking, and it was a good and reliable scale.[20, 21]. Other authors have used a version of AHP and group decision as well [22]. In this paper, an AHP method based on index interval scale is proposed, which combines index scale with interval scale effectively. Meanwhile, group decision-making theory is introduced to construct a judgment matrix through multiple experts to eliminate the judgment bias caused by personal preferences. It is applied to civil aviation passenger risk assessment to make the evaluation results more scientific and reliable.

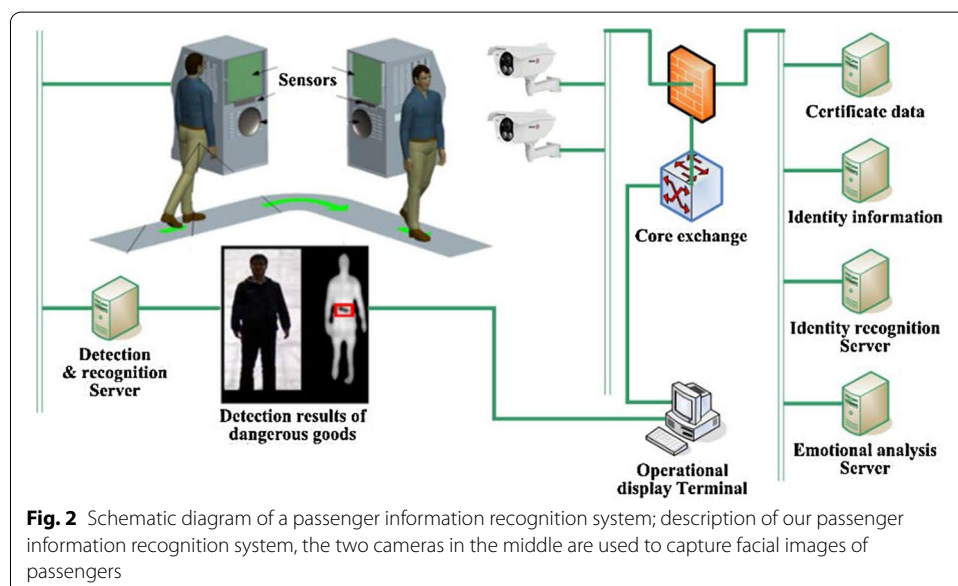
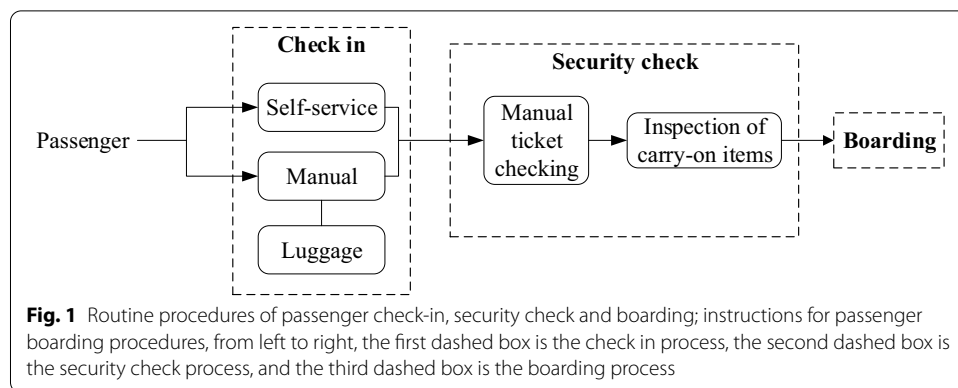
Machine learning is one of the most important breakthroughs in the field of artificial intelligence, such as speech recognition, computer vision, video analysis and multimedia [23]. In this paper, we employ machine learning to perform face recognition and emotion analysis, in a bid to effectively and efficiently conclude the passenger's risk level.

Expression recognition is similar to face recognition. The difference is that facial recognition uses facial features for face recognition, while facial expression recognition uses facial features to identify types of human emotions. The two systems can be complementary because the facial recognition system recognizes the face owner, and the facial emotion recognition system recognizes the emotion expressed by the facial owner. The biggest difference between deep learning and traditional pattern recognition methods is that it automatically learns features from big data, rather than features designed by hand. The characteristics of manual design mainly rely on the a priori knowledge of the designer, and it is difficult to take advantage of big data. Due to the dependence on manual adjustment of parameters, only a small number of parameters are allowed in the design of features. Therefore, in the airport security inspection, the proposed new system will process the collected face information and use machine learning to perform face recognition and emotion analysis to evaluate the passenger's risk level.

The remainder of this paper is organized as follows. Section II introduces the new security check system. Three new security technologies based on 5G technology and machine learning are introduced, including face recognition, millimeter-wave security detector and emotional analysis. Section III examines the improved AHP method based on group decision. Section IV proposes the new model of graded security check. In Section V, four cases are given to illustrate the results of passenger security risk assessment under different circumstances and methods. Finally, Section VI concludes the paper.

1.1 A novel design of security check system

The proposed novel design of security check system is mainly composed of three technologies, including facial recognition, millimeter-wave human security detector and potential emotion analysis. The proposed solution combines three new technologies with big data of civil aviation passengers to conduct risk assessment on passengers and adopt different security procedures for passengers with different risks. Ultimately, the goal of improving airport security inspection efficiency and resource utilization, and saving passengers' time will be facilitated.



1.2 Security check system at airports

One of the duties of civil aviation security checks is to carry out safety check on passengers and their luggage, including four links: certificate check, personal check, check-in of carry-on luggage and checked luggage [24]. Figure 1 shows the routine procedures of passenger check-in, security check and boarding. It can be seen that the routine security check process uses the same check steps for all passengers, resulting in long waiting time and low efficiency. If we use a variety of new security technologies and large data analysis of civil aviation passengers, classify passengers through risk assessment, use limited security resources for high-risk passengers and simplify the security check process for some low-risk "frequent passengers," we can improve security check efficiency and improve passenger travel experience under the condition of controllable risk.

Figure 2 shows the schematic diagram of a passenger information recognition system based on a variety of new security technologies. The hardware of the system is usually placed inside the terminal building. Based on three new security technologies: face recognition, through-type millimeter-wave human body security detector and potential

emotional analysis, millimeter-wave human body security channel and face recognition camera are set in the relevant area before passengers enter the conventional security channel to capture the whole body millimeter-wave radar image and face image information of passengers from different angles. The above information is tested, identified and analyzed to realize passenger risk classification and risk information warning. The basic functions of three new security technologies are described below.

1.3 5G-IoT-based new security technologies

1.3.1 The basics of 5G and IoT

5G mobile communication has many characteristics such as high speed, large capacity and low latency. In the IoT, high-quality and real-time video data transmission is often required. Especially in the 5G communication system, many IoT terminal devices will play an important role, such as autonomous driving or a surveillance system with a high-definition camera. Due to the heterogeneity of equipment and services, a multilayer architecture will be adopted in 5G networks. The emergence of 5G technology is related to the demand for connection between people and devices, so new technologies and new services that can meet such large-scale connection traffic needs are needed. The key technologies currently involved in 5G include machine-to-machine communication, device-to-device communication (D2D), cloud computing, millimeter-wave communication and IoT [25].

IoT is a potential technology that intends to realize the interconnection of all things. With the development of technology, the popularity of small and inexpensive computing devices with sensing and communication functions is paving the way for the widespread application of IoT technology [26, 27].

In the system of this paper, we deploy high-precision cameras and millimeter-wave detectors at the airport as IoT terminals to monitor airport passengers in real time, and transmit data through 5G communication channels to realize face monitoring and dangerous goods recognition.

1.3.2 Face recognition cameras and millimeter-wave security detector

Face recognition system uses face detection, tracking and recognition algorithm, through a reasonable layout of face recognition cameras, when passengers enter and exit the millimeter-wave human body security channel, face capture and recognition are carried out. By connecting with the database of public security license and identity information resources, the fugitive criminals can be charged in advance and warned in real time, grasp the dynamics in real time and quickly lock the suspect's trajectory [28].

By detecting the millimeter-wave signal of natural radiation of the human body and personal belongings, the millimeter-wave human body security detector can detect and identify hidden dangerous goods quickly, safely and efficiently [29]. The special passageway for human security check is auxiliary equipment used in conjunction with millimeter-wave human security instrument. It is 4.5 m in length, 4.5 m in width and 2.8 m in height. It provides a special passageway for large passenger flow. It does not touch or interfere with human behavior, and can simultaneously detect a variety of metals and non-metals, and identify all kinds of dangerous goods, such as guns, ammunition, explosives and knives.

1.4 Machine learning-based new security technologies

1.4.1 *The basics of emotion analysis technology*

The face is the information most used to identify the human body. At the same time, the face is also an important medium for expressing a person's mental state and a vital way to spread human emotional information and coordinate interpersonal relationships. Facial expression recognition is an important part of face recognition technology [30]. In recent years, it has received extensive attention in the fields of human–computer interaction, security, robot manufacturing, automation, medical, communication and driving, and has become a hotspot in academia and industry.

Although latent emotion analysis technology still uses image processing technology, it is different from face recognition in that it extracts the movement of facial muscles. Potential emotions are usually spontaneous movements controlled by vestibular organs. Therefore, the subtle movements of muscle groups can be used to judge the potential emotions of target people and to some extent reveal the psychological activities of people [31]. Potential emotional analysis system can use the face image captured by face recognition system to acquire and analyze the emotional state (aggressiveness, tension and pressure) of each target face, calculate its risk level comprehensively and use it for subsequent risk assessment. At the same time, it can capture the face image beyond the warning value and display the results on the screen through numbers and colors.

1.4.2 *Machine learning-based facial expressions recognition*

Machine learning is an important concept in the field of artificial intelligence. It has achieved great success in many fields such as speech recognition, natural language processing, computer vision, image and video analysis and multimedia. Deep learning plays a very important role in the field of object recognition, in which face recognition is an important breakthrough. The biggest challenge of face recognition is how to distinguish between intra-class changes caused by factors such as light, posture and expression and inter-class changes caused by different identities. These two types of change distributions are nonlinear and extremely complex, and traditional linear models cannot effectively distinguish them. The purpose of deep learning is to obtain new feature representations through multilayer nonlinear transformation.

Convolutional neural network (CNN) is the most commonly used deep learning method in face recognition and emotion analysis. The main advantage of the deep learning is that it can be trained with a large amount of data [32]. This method does not need to design specific features that are robust to different types of intra-class differences (such as lighting, posture, facial expressions and age), but can learn them from the training data. The main shortcoming of deep learning methods is that they need to use very large data sets for training, and these data sets need to contain enough changes so that they can be generalized to unseen samples. Fortunately, some large-scale face data sets containing natural face images have been published and can be used to train CNN models. Therefore, in airport scenarios, using machine learning to carry out face recognition and emotion analysis on passengers has practical significance.

2 Improved AHP method based on group decision

In this part, the improved AHP method based on group decision-making is described in detail, called the GD-AHP method. First, the index interval number scaling method is introduced, and then, the calculation method of expert weight and the establishment process of expert group decision-making matrix are given.

2.1 Exponential interval scaling method

Weber–Fechner’s law [33, 34] holds that psychological quantity is a logarithmic function of external stimulus, that is, when the stimulus intensity increases in geometric series, the intensity of sensation increases in arithmetic series. According to this theorem, if the importance degree of index a_i relative to a_j is divided into nine grades, which are "equal important," "slightly important," "obvious important," "very important," "extremely important" and their intermediate grade, respectively, and the nine grades are described, respectively, by integers $t=0-8$, then is the relationship between a_{ij} , the objective importance ratio of index a_i to a_j , and t is

$$a_{ij} = c^t, \quad (1)$$

where c is the ratio constant of importance degree of two adjacent levels and $t=0, \pm 1, \pm 2, \dots, \pm 8$. It is generally believed that it is appropriate to use 9 as the limit of the ratio of importance of two factors, i.e., the expression of "extreme importance." Then, we get $c = \sqrt[4]{3} \approx 1.316$ from $a_{ij}=c^8=9$.

The exponential scaling method can achieve consistency with the thinking judgment, but the comparison judgment result is still a definite value. In order to adapt to the fuzziness and randomness of the evaluation process, interval numbers are used to quantify people’s subjective judgments. At this time, all elements in the judgment matrix are exponential interval numbers.

$\tilde{A} = (\tilde{a}_{ij})_{n \times n}$ is called the interval matrix based on exponential scaling (i.e., exponential interval number matrix), if the following are satisfied:

1. $\tilde{a}_{ij} = [a_{ij}^L, a_{ij}^R]$, where \tilde{a}_{ij} is the interval matrix, a_{ij}^L and a_{ij}^R both exponential scales, $a_{ij}^L = c^{t_{ij}^L}$, $a_{ij}^R = c^{t_{ij}^R}$;
2. $\tilde{a}_{ii} = [1, 1]$;
3. $\tilde{a}_{ji} = \frac{[1,1]}{\tilde{a}_{ij}} = \left[\frac{1}{a_{ij}^R}, \frac{1}{a_{ij}^L} \right]$;
then $\tilde{T} = (t_{ij})_{n \times n}$ is the subjective sensory judgment matrix corresponding to \tilde{A} , where $\tilde{t}_{ij} = [t_{ij}^L, t_{ij}^R]$, $\tilde{t}_{ii} = [0, 0]$, and $\tilde{t}_{ij} = -\tilde{t}_{ji}$.

In order to keep the level of ambiguity in judgment consistent, the interval width of each element in \tilde{T} is set to 2, i.e., $t_{ij}^R - t_{ij}^L = 2$, then the corresponding index interval values are obtained as $[c^{t-1}, c^{t+1}]$, in which $t = 0, 1, 2, 3, \dots, 8$. The corresponding relationship between index interval scales and natural language descriptions is shown in Table 1.

From Table 1, we can see that the greater the difference of importance levels, the greater the distance between the scale intervals, the greater the uncertainty of the scale, which conforms to the rule of human thinking. The weights of each index are

Table 1 Index interval number scale

Natural language description	Scale interval \tilde{a}_{ij}
Equal important	$[c^{-1}, c^1] = [0.760, 1.316]$
Slightly important	$[c^1, c^3] = [1.316, 2.280]$
Obvious important	$[c^3, c^5] = [2.280, 3.948]$
Very important	$[c^5, c^7] = [3.948, 6.839]$
Extremely important	$[c^7, c^9] = [6.839, 11.845]$
Intermediate grades	$[c^0, c^2], [c^2, c^4], [c^4, c^6], [c^6, c^8]$

the average and standardized values of all elements in the row corresponding to the judgment matrix.

2.1.1 Calculation of expert weight

In the actual evaluation, a single expert often cannot fully reflect the objective facts. Therefore, it is necessary to synthesize the opinions of multiple experts, which leads to the problem of group decision-making. The process of group decision-making is to unify the differences of expert opinions and minimize the inconsistency between the results of group decision-making and individual preferences [35, 36].

Set-valued statistics is an effective way to deal with uncertainty evaluation index. The evaluation index set of the evaluation system is defined as $X = \{x_1, x_2, \dots, x_r, \dots, x_n\}$, and the assessment experts are $S = \{s_1, s_2, \dots, s_r, \dots, s_n\}$. For each criterion $x_r (x_r \in X)$, interval estimates given by experts $s_r (s_r \in S)$ are $[\mu_{rk}^L, \mu_{rk}^R] (k = 1, 2, \dots, m)$, in this way, a m -dimensional set-valued statistical sequence can be formed. Add these m intervals together, and define $\mu_r^{\min} = \min_{k=1}^m (\mu_{rk}^L)$ and $\mu_r^{\max} = \max_{k=1}^m (\mu_{rk}^R)$, so the m experts' judgment of the index x_r forms a random distribution on the number axis on the interval of $[\mu_r^{\min}, \mu_r^{\max}]$.

$$\bar{F}_{x_r}(\mu) = \sum_{k=1}^m \lambda_k \cdot F_{[\mu_{rk}^L, \mu_{rk}^R]}(\mu), \quad (2)$$

where

$$F_{[\mu_{rk}^L, \mu_{rk}^R]}(\mu) = \begin{cases} 1, & \mu \in [\mu_{rk}^L, \mu_{rk}^R] \\ 0, & \text{else} \end{cases}$$

λ_k is the weight of the k th expert and $\sum_{k=1}^m \lambda_k = 1$. According to the above formula, the position of the center of gravity of the random set $\bar{\mu}_r$ can be obtained and used as the comprehensive evaluation value of group decision-making of index x_r

$$\bar{\mu}_r = \frac{\int_{\mu_r^{\min}}^{\mu_r^{\max}} \mu \cdot \bar{F}_{x_r}(\mu) d\mu}{\int_{\mu_r^{\min}}^{\mu_r^{\max}} \bar{F}_{x_r}(\mu) d\mu}, \quad (3)$$

The above formula is simplified as

$$\bar{\mu}_r = \frac{1}{2} \cdot \frac{\sum_{k=1}^m \lambda_k \left[(\mu_{rk}^R)^2 - (\mu_{rk}^L)^2 \right]}{\sum_{k=1}^m \lambda_k (\mu_{rk}^R - \mu_{rk}^L)}, \quad (4)$$

The determined $\bar{\mu}_r$ is the comprehensive evaluation value of index x_r by group decision-making after considering the weights of experts.

Expert weights can be indirectly reflected by the judgment matrix constructed by experts, which is embodied in the difference between individual preference information and comprehensive preference information of experts. In order to quantitatively reflect this difference, the deviation degree of the two interval numbers, $\tilde{a} = [a^L, a^R]$ and $\tilde{b} = [b^L, b^R]$, is defined as

$$\delta(\tilde{a}, \tilde{b}) = \frac{|a^L - b^L| + |a^R - b^R|}{b^R - b^L}, \quad (5)$$

When establishing the judgment matrix, the judgment interval of the expert k to index x_r is $\tilde{\mu}_{rk} = [\mu_{rk}^L, \mu_{rk}^R]$, then the average evaluation interval of all m experts for the index x_r is as follows

$$\tilde{\mu}_r^* = \frac{1}{m} \sum_{k=1}^m \tilde{\mu}_{rk} = \left[\frac{1}{m} \sum_{k=1}^m \mu_{rk}^L, \frac{1}{m} \sum_{k=1}^m \mu_{rk}^R \right], \quad (6)$$

By substituting the above formula into formula (5), the relative deviation δ_{rk} between $\tilde{\mu}_{rk}$ and $\tilde{\mu}_r^*$ can be obtained as

$$\delta_{rk} = \frac{\left| \tilde{\mu}_{rk}^L - \frac{1}{m} \sum_{k=1}^m \mu_{rk}^L \right| + \left| \tilde{\mu}_{rk}^R - \frac{1}{m} \sum_{k=1}^m \mu_{rk}^R \right|}{\frac{1}{m} \sum_{k=1}^m \mu_{rk}^R - \frac{1}{m} \sum_{k=1}^m \mu_{rk}^L}, \quad (7)$$

For different indicators, the deviation degree of the same expert's evaluation results is different. It is generally believed that there is a consistent trend in the subjective rational judgment of experts, and the generation of inconsistent evaluation matrix can be considered as the result of the interaction of many random disturbances.

Assuming that the relative deviation between the evaluation interval of each index given by expert k and the total weighted evaluation interval of corresponding indexes is δ_k , the following assumptions could be made: when the number of evaluation indexes is infinite, the deviation of each index obeys a normal distribution $\delta_k \sim N(0, \sigma_k^2)$.

Given parameter $\mu = 0$, we can obtain the maximum likelihood estimator of σ_k^2 , which represents the deviation between expert k 's judgment and expert group's judgment. The likelihood function is

$$L(\sigma_k^2) = \prod_{r=1}^n \frac{1}{\sqrt{2\pi}\sigma_k} \exp \left[-\frac{\delta_{rk}^2}{2\sigma_k^2} \right], \quad (8)$$

So, the maximum likelihood estimator of σ_k^2 is

$$\sigma_k^2 = \frac{1}{n} \sum_{r=1}^n \delta_{rk}^2, \quad (9)$$

where σ_k^2 reflects the degree of deviation between expert k 's judgment and expert group's judgment. The smaller the value of σ_k^2 , the higher the expert's judgment level, the greater the weight, vice versa. Therefore, the weight of expert k can be calculated according to the following formula

$$\lambda_k = \frac{\frac{1}{\sigma_k^2 + 1}}{\sum_{r=1}^m \frac{1}{\sigma_k^2 + 1}}, \quad (10)$$

2.1.2 Establishment of expert group decision matrix

The steps needed to calculate the expert group decision matrix are as follows:

1. Subjective perception judgment matrix given by experts is $\tilde{T}_k = (\tilde{t}_{ij}^k)_{n \times n}$. Since \tilde{T}_k is a reciprocal matrix, only the upper triangular matrix of the matrix (excluding the diagonal elements) can be considered to form a set-valued statistical sequence of evaluation indices with a total number of $n' = n(n-1)/2$.
2. Calculate the weights of experts. The synthetic evaluation value of group decision-making with n' indexes is obtained by formula (4) is $\bar{\mu}_1, \bar{\mu}_2, \dots, \bar{\mu}_r, \dots, \bar{\mu}_{n'}$.
3. Taking the n' values as the midpoint, the interval numbers of n' intervals with width of 2 are obtained, which are denoted as.

$$\tilde{v}_r = [\bar{\mu}_r - 1, \bar{\mu}_r + 1], \quad (11)$$

where \tilde{v}_r is called the comprehensive evaluation interval of group decision-making with index x_r . And each \tilde{v}_r is reduced to group decision-making judgment matrix $\tilde{T}^* = (\tilde{t}_{ij}^*)_{n \times n}$.

4. Finding expert group decision-making matrix $\tilde{A}^* = (\tilde{a}_{ij}^*)_{n \times n}$, where

$$\tilde{a}_{ij}^* = c \tilde{t}_{ij}^*, \quad (12)$$

In the formula, the ratio constant of importance is taken as $c = \sqrt[4]{3}$. The judgment matrix of expert group decision-making, \tilde{A}^* , is obtained, and the weight of each index can be calculated according to the method of Sect. 3.1

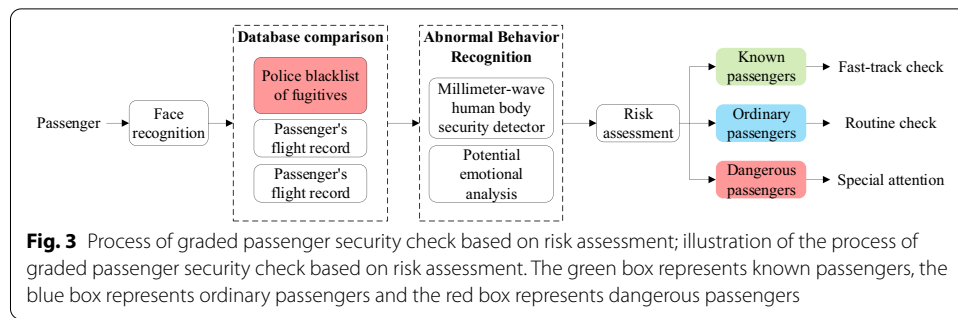
According to the above method, the index weight of each level element in AHP model can be obtained. Assuming that there are m indicators in a hierarchical unit of the AHP model, $w_i^{(0)}$ is the weight of index i in the unit, and s_i is the evaluation value of index i , so the evaluation result of the unit is

$$V_0 = \sum_{i=1}^m w_i^{(0)} s_i, \quad (13)$$

Through step by step synthesis, the overall evaluation results can be obtained.

2.1.3 A model of graded security check with cutting-Edge technologies

By adopting the aforementioned new security technologies, this section first presents a novel passenger grading security check process based on risk assessment, followed by

**Table 2** Graded security check and disposal

Categories	Specific disposal methods
Fast-track check	No need to take out laptop, toiletries, cameras, etc., before X-ray machine luggage check
Routine check	Before X-ray machine luggage check, take out notebook laptop, toiletries, cameras, etc. When suspicious things are found, open the bag for check, and combine metal detector with manual physical examination
Special attention	100% open luggage check, 100% metal detector combined with manual physical examination, 100% removing belt and shoe removal check, 100% explosion-proof check, if necessary, quickly lock its track and transfer it to the police for processing

our proposed GD-AHP method in the second step to assess passenger risk. Finally, we develop the security check efficiency and airport implementation scheme.

2.1.4 Graded passenger security check model based on risk assessment

Figure 3 illustrates the process of graded passenger security check based on risk assessment. First, face recognition technology is used to confirm the identity of the passenger. By comparing the databases, it is clear whether the passenger belongs to the police blacklist of fugitives, and the passenger's flight record and credit record are obtained. Then, by means of the millimeter-wave human body security detector and potential emotional analysis technology, the passenger is confirmed whether he carries or has dangerous goods in his checked luggage. The potential emotional states such as aggressiveness, tension and stress are obtained. Based on the passenger history data and real-time status information obtained by the above two steps, the comprehensive risk assessment is carried out. According to the risk level, the passengers are divided into known passengers, ordinary passengers and dangerous passengers, which are handled separately by disposals of fast-track check, routine check and special attention (Table 2).

2.1.5 Index system and risk assessment method

First, the GD-AHP method is applied to civil aviation passenger risk assessment, and then, the graded security check risk index system and the scoring calculation method of single index are given. Finally, the classification criteria of different security check grades are proposed.

2.1.5.1 Weight calculation of index system A risk assessment model of civil aviation passengers based on new security technology is established, and the index weights of each level are calculated by this method. The model is divided into two levels. The first-

Table 3 Expert weight

Expert no.	λ_1	λ_2	λ_3	λ_4	λ_5	λ_6
Comprehensive weight	0.1570	0.1712	0.1766	0.1712	0.1527	0.1712

Table 4 Weights of indicators on the first level

Indicator	E_1	E_2	E_3
First-level weight (%)	62.3	17.4	20.3

level indicators include personnel information (E_1), civil aviation passenger information record (E_2) and abnormal behavior identification results (E_3). Among them, E_2 has two secondary indicators of civil aviation passenger flight record (E_{21}) and civil aviation passenger credit record (E_{22}), and E_3 has two secondary indicators, namely through millimeter-wave human body security detector (E_{31}) and potential emotional analysis (E_{32}).

The following three indicators at the first level (personnel information monitored by Police, information records of civil aviation passengers and identification results of abnormal behavior) are taken as examples to illustrate the calculation process of weight with the GD-AHP method.

1. By comparing and judging the indicators on the first level, the subjective sensory judgment matrix filled out by six security experts is as follows:

$$\begin{array}{lll}
 \text{Expert 1 :} & \text{Expert 2 :} & \text{Expert 3 :} \\
 \begin{bmatrix} [0,0] & [3,5] & [3,5] \\ & [0,0] & [-3,-1] \\ & & [0,0] \end{bmatrix} & \begin{bmatrix} [0,0] & [3,5] & [4,6] \\ & [0,0] & [-1,1] \\ & & [0,0] \end{bmatrix} & \begin{bmatrix} [0,0] & [3,5] & [3,5] \\ & [0,0] & [-1,1] \\ & & [0,0] \end{bmatrix} \\
 \text{Expert 4 :} & \text{Expert 5 :} & \text{Expert 6 :} \\
 \begin{bmatrix} [0,0] & [4,6] & [3,5] \\ & [0,0] & [-1,1] \\ & & [0,0] \end{bmatrix} & \begin{bmatrix} [0,0] & [3,5] & [4,6] \\ & [0,0] & [-3,-1] \\ & & [0,0] \end{bmatrix} & \begin{bmatrix} [0,0] & [4,6] & [3,5] \\ & [0,0] & [-1,1] \\ & & [0,0] \end{bmatrix}
 \end{array}$$

2. The expert weights are calculated according to formula (10). The results are shown in Table 3.
3. Taking the upper triangular elements of the matrix, there are three evaluation indicators, weighted to get the subjective sense judgment matrix of group decision-making as follows:

$$\begin{bmatrix} [0,0] & [3.3425, 5.3425] & [3.3240, 5.3240] \\ & [0,0] & [-1.6194, -0.3806] \\ & & [0,0] \end{bmatrix}$$

4. Computing the expert group decision matrix \tilde{A}^* based on formula (12):

$$\begin{bmatrix} [1,1] & [2.5043, 4.3376] & [2.4916, 4.3156] \\ [0.2305, 0.3993] & [1,1] & [0.6410, 1.1102] \\ [0.2317, 0.4013] & [0.997, 1.5601] & [1,1] \end{bmatrix}$$

5. Calculate the weight of each index, and the results are as follows (Table 4).

Based on the reality of civil aviation passenger security check with new security technologies, the above process synthesizes the opinions of different experts and quantifies reasonably the consistency of judgment and thinking and the fuzziness of judgment, so it is more scientific and reliable. It can be seen that the importance of personnel information indicators that public security focuses on is significantly higher than the other two indicators, and its weight accounted for 62.3%, and there is no longer a secondary indicator. Face recognition technology is used to compare passenger's face information with the blacklist of police pursuers. Once successful, all item scores are deducted and alarmed.

According to the above method, the weights of other levels in the AHP model can be obtained. Among them, E_{21} and E_{22} are two secondary indicators of expert group decision matrix.

$$\begin{bmatrix} [1, 1] & [0.4386, 0.760] \\ [1.316, 2.280] & [1, 1] \end{bmatrix}$$

The results show that the secondary weights of the above two secondary indicators are 36.4% and 63.6%, respectively. It can be seen that the importance of the civil aviation passenger credit record index E_{22} is higher than that of the civil aviation passenger flight record index E_{21} , which reflects the high attention paid to passenger credit records.

Similarly, the expert group decision matrix of E_{31} and E_{32} is

$$\begin{bmatrix} [1, 1] & [2.280, 3.948] \\ [0.2533, 0.4386] & [1, 1] \end{bmatrix}$$

The secondary weight of dangerous goods is 75.4%, the highest weighting after E_1 , showing its importance in the security check evaluation. The emotional status indicator, at 24.6%, is of less importance.

2.1.5.2 Graded security check risk index system and score calculation Table 5 shows the first, second and comprehensive weights of the first and second level indexes in the risk assessment index system of civil aviation passenger graded security check. The full score of all the single second level indexes is set to 100, and the cumulative penalty points are calculated according to the standards in Tables 6, 7, 8 and 9, respectively, until the penalty is completed.

The score of E_{21} is deducted according to the standard of Table 6. For passengers who have taken more than 60 flights in 3 years (denoted by N_{pf}), the score of E_{21} is full. It shows that frequent passengers who take more flights are familiar with the requirements of civil aviation security check, which can simplify the requirements of civil aviation security check.

The score of E_{22} is calculated according to the standard of Table 7. The scores of E_{22} are deducted for the different severity of civil aviation passengers' violation of civil aviation regulations, and for the more serious acts, the total score is deducted, where "Others" mean the dishonesty or irregularities of passengers not taken into account.

The score of E_{31} is calculated according to the standard of Table 8. The score is deducted according to the result of detection and identification of the millimeter-wave

Table 5 Graded security check risk index system and score calculation method

First level index	First level weight (%)	Second level index	Second level weight (%)	Synthetic weight (%)	Score calculation method
Personnel information focused on by Police (E_1)	62.3	Personnel information focused on by Police	100	62.3	If they are on the blacklist of fugitives, 100 points will be deducted and an alarm will be issued directly
Civil aviation passenger information record (E_2)	17.4	Civil aviation passenger flight records (E_{21})	36.4	6.3	Penalty of score according to Table 6, up to zero
		Civil aviation passenger credit records (E_{22})	63.6	11.1	Penalty of score according to Table 7, up to zero
Abnormal behavior recognition results (E_3)	20.3	Through-type millimeter-wave human body security detector (E_{31})	75.4	15.3	Penalty of score according to Table 8, up to zero
		Potential emotional analysis (E_{32})	24.6	5.0	Penalty of score according to Table 9, up to zero

Table 6 Civil aviation passenger record penalty standard

No.	Score	Penalty
1	$N_{pf} \geq 60$	0
2	$40 < N_{pf} < 60$	20
3	$20 < N_{pf} \leq 40$	40
4	$5 < N_{pf} \leq 20$	60
5	$0 < N_{pf} \leq 5$	80
6	$N_{pf} = 0$	100

Table 7 Civil aviation passenger credit record penalty standard

No.	Infraction	Penalty
1	Fabrication and deliberate dissemination of false terrorist information related to civil aviation air defense safety	100
2	Theft of other people's goods on board an aircraft	100
3	Use forgery, alteration or fraudulent use of other people's identity documents and flight vouchers	100
4	Carry or consign dangerous goods, contraband goods and controlled articles prescribed by national laws and regulations	100
5	Blockage, seizure, impact check-in counter, security access, boarding gate (access)	50
6	To forcibly occupy or intercept aircraft, forcibly break into or impact aircraft cockpits, runways and aprons	50
7	To obstruct or incite others to obstruct aircrew, security check, check-in and other civil aviation personnel from performing their duties and to carry out or threaten to carry out personal attacks	50
8	Use of open fire, smoking, illegal use of electronic equipment in aircraft, disobedience to dissuasion	40
9	The act of occupying seats, luggage racks, fighting, provoking trouble, deliberately damaging, stealing, unlawfully opening aircraft or aviation facilities and equipment to disrupt cabin order	30
10	Others	30

Table 8 Through-type millimeter-wave human body security detector penalty standard

No	Infraction	Penalty
1	Guns, ammunition, explosives and controlled knife	100
2	Alcohol, general knife	60
3	Other general contrabands	40

Table 9 Potential emotional analysis penalty standard

No	Infraction	Penalty
1	The aggressiveness index value is higher than the set threshold	100
2	The tension index value is higher than the set threshold	80
3	The pressure index value is higher than the set threshold	60

human body security detector. The risk level of guns, ammunition and explosives is the highest. Once found, the total score is deducted.

The score of E_{32} was deducted according to the standard of Table 9, and the score was deducted according to the result of potential emotional analysis. When the analysis results exceed the set threshold, the scores are deducted according to the risk level, and the scores from high to low are aggression, tension and stress.

The scores of all secondary indicators constitute the score vectors \mathbf{G}^{1-2} .

2.1.5.3 Graded security check standard Based on the weights and corresponding scores of all secondary indicators of security check risk, the total score P of comprehensive risk assessment is obtained by weighting, as follows

$$P = \text{sum}(\mathbf{G}^{1-2} \cdot \mathbf{W}^{1-2}), \quad (14)$$

where \mathbf{G}^{1-2} represents the vector composed of the scores of all secondary indicators and \mathbf{W}^{1-2} represents the vector composed of the weights of all secondary indicators. Table 10 gives the classification criteria of known passengers, ordinary passengers and dangerous passengers, and explains the basis of the comprehensive scoring range of each grade.

The criteria of passenger risk classification are mainly based on the following considerations:

1. Set strict standards for "known passengers." Only those "frequent passengers" who meet the requirements of the number of flights, have good credit records and have not found any abnormal in the passing millimeter-wave security detector and potential mood analysis can pass through customs quickly.
2. Dangerous goods (which can be found by millimeter-wave human body security detector) are the second highest risk factor, so if dangerous goods are found, 15.3 points will be deducted, putting the passenger in the dangerous passenger category.

Table 10 Risk classification criteria

Risk level	Scoring range	Explanation
Known passengers (very low)	100	Over the past 3 years, the cumulative number of flights was no less than 60, the credit record was good, and no abnormalities were found by the through-type millimeter-wave security detector and potential emotional analysis
Ordinary passengers (low)	(85, 100)	Over the past 3 years, the cumulative number of flights was less than 60 (deducting 1.25–6.3 points), contraband or bad mood was found in the millimeter-wave security device (deducting 0–9.18 points), and potential emotional analysis (deducting 0–5 points)
Dangerous passengers (very low)	[0, 85]	On the "blacklist of fugitives" of police (deducted 100 points), there are many bad credit records of civil aviation (deducted 11.1 points), and high-risk dangerous goods or bad mood are found by the millimeter-wave security detector (deducted 15.3 points) and potential emotional analysis (deducted 5 points)

3. If passengers in the credit record, through millimeter-wave human body security instrument, potential emotional analysis and other indicators link, the cumulative score is more than 15 points, the total score is less than 85 points, it will also be divided into "dangerous passengers" for "focus," reflecting the basic principle of "safety first."

2.1.6 Security check efficiency

The passenger information recognition system is set up before routine security checks and carries out risk classification for different passengers. Because the system is suitable for large passenger flow, passengers do not need to stop, and it will not increase the security check time itself. This system can identify and fast-track low risk passengers to minimize delays for this group, significantly improving the flight experience of this part of the passengers.

According to the rules established in this paper, the proportion of low-risk passengers is at least 10%, and their security check time is about 30% of the routine security check, which can improve the efficiency of security check to a certain extent. With the continuous use of the system, the proportion of low-risk passengers will also rise, further improving the efficiency of security checks.

A possible check process is designed as follows: Two gates can be installed in the waiting area. After identification and risk assessment, the passengers hold the ID card or passport at the first gate, so their identity information is read and correlated with their risk assessment results. For frequent passengers with good safety credit, the entry gate will guide them to enter the "fast-track check" through the second gate. For those passengers with higher risk, the entry gate will guide them into the "routine check" channel or "special check" channel.

At present, facial recognition technology should be sufficient, but even if it fails, it can be compensated for by ID card recognition when passengers pass through the first gate. When it comes to passenger privacy protection, all passenger information identification systems encrypt passenger's personal information. For example, after millimeter-wave

Table 11 Risk assessment results and disposal methods of case 1

2nd level index	Comprehensive weight (%)	Sub-score	Score	Explanation and disposal
Personnel information focused on by police	62.3	100	100	Over 60 flights were taken in the last 3 years, and the result was "known passengers," which should be handled according to "fast-track check"
Civil aviation passenger flight records	6.3	100		
Civil aviation passenger credit records	11.1	100		
Through-type millimeter-wave human body security detector	15.3	100		
Potential emotional analysis	5.0	100		

Table 12 Risk assessment results and disposal methods of case 2

Second level index	Comprehensive weight (%)	Sub-score	Score	Explanation and disposal
Personnel information focused on by police	62.3	100	87.58	The passenger took the flight for the first time in the last 3 years, carried suspected contraband, so processed according to the "routine check"
Civil aviation passenger flight records	6.3	0		
Civil aviation passenger credit records	11.1	100		
Through-type millimeter-wave human body security detector	15.3	60		
Potential emotional analysis	5.0	100		

security detector imaging, cartoon pictures will be used to replace sensitive parts of the human body.

3 Results and discussion

In this part, four cases are given to illustrate the results of passenger security risk assessment under different circumstances and the corresponding disposal methods.

3.1 Case 1: Known passengers

As shown in Table 11, the passenger has taken more than 60 flights in 3 years, belonging to "frequent passengers" without bad civil aviation credit records, and no his or her abnormalities were found by the through-type millimeter-wave security detector and potential emotional analysis. All the scores are "100," and the comprehensive risk assessment results are "100," belonging to "known passengers," who are handled according to the "fast-track check" as illustrated in Table 1.

3.2 Case 2: Ordinary passengers

As shown in Table 12, the passenger took the plane for the first time in the last 3 years (with the second level score of "0") without any bad credit record. During the check by the millimeter-wave security detector, it was found that the passenger carried "suspected liquids exceeding 100 ml" (with the second level score of "60"), and the comprehensive

Table 13 Risk assessment results and disposal methods of case 3

Second level index	Comprehensive weight (%)	Sub-score	Score	Explanation and disposal
Personnel information focused on by police	62.3	0	0	Successfully found on the police blacklist of the fugitives, so judged as "dangerous passengers" and transferred to the airport police organs
Civil aviation passenger flight records	6.3	–		
Civil aviation passenger credit records	11.1	–		
Through-type millimeter-wave human body security detector	15.3	–		
Potential emotional analysis	5.0	–		

Table 14 Risk assessment results and disposal methods of case 4

Second level index	Comprehensive weight (%)	Sub-score	Score	Explanation and disposal
Personnel information focused on by police	62.3	100	73.4	When it is found that the passenger carries "suspected explosives" and has high risk of bad mood, it is judged to be "dangerous passengers," and the disposal procedure of "special attention" is initiated, which should be sent to the airport police organs for disposal when necessary
Civil aviation passenger flight records	6.3	0		
Civil aviation passenger credit records	11.1	100		
Through-type millimeter-wave human body security detector	15.3	0		
Potential emotional analysis	5.0	0		

risk assessment result was "87.58," who belonged to "ordinary passengers" and was handled according to "routine check" as illustrated in Table 1.

3.3 Case 3: Dangerous passengers (fugitives)

As shown in Table 13, once the passenger was successfully found on the police blacklist of the fugitives after face recognition, all the index scores were reduced to zero, so they were judged as "dangerous passengers." Face recognition system quickly locked the trajectory of the passenger's movement, and related information transferred to the airport police organs for further treatment.

3.4 Case 4: Dangerous passengers (non-fugitives)

As shown in Table 14, the passenger took the first flight in 3 years (with a single score of "0") and had no bad credit record. It was found that the passenger carried "suspected explosives" (with the second level score of "0") in the millimeter-wave security detector test, and after potential emotional analysis, it was found that the aggression and tension index values exceeded the set threshold (with the second level score of "0"). The comprehensive risk assessment result is "73.4," which belongs to "dangerous passengers" and should be handled according to "special attention" as illustrated in Table 1.

4 Conclusions

In this paper, a passenger risk assessment scheme based on GD-AHP is proposed for graded security check by combining several new security technologies and the large historical data of civil aviation passengers. The passenger differential security check mode, as proved in this work, can bring better travel experience to passengers. Most passengers can avoid the second security check such as open package check and personal examination, shorten the waiting time of passengers queuing and improve the efficiency of security check. At the same time, this mode not only benefits the passengers, but also improves the airport security resources allocation. In fact, the potential danger of most passengers is relatively low. If strict and tedious security checks are carried out, it will undoubtedly increase the investment of airport equipment, personnel and funds, resulting in waste of resources. Safety is the primary task of civil aviation security, and by using a number of new security technologies, this work can improve the efficiency of security check and service quality on the premise of ensuring security.

At present, there are few materials for evaluating passenger risk grade factors, and there are relatively few in actual implementation. Therefore, the applicability and feasibility of the risk classification system proposed in this article can be further studied and optimized in the future to make it suitable for the actual application of the airport. Moreover, due to the limitation of practical conditions, the sample of passenger data collected in this article is small. In future work, it is expected that big data technology will be used to test our proposed method and help improve the accuracy of passenger classification.

Abbreviations

5G: Fifth generation; AHP: Analytic hierarchy process; IoT: Internet of things; TSG: Threat screening game; D2D: Device-to-device communication; CNN: Convolutional neural network.

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Authors' contributions

Conceptualization, WC and YH; Methodology, WC and HY; Software, WC and XL; Supervision, WC and JL; Validation, HY and XL; Writing—original draft, WC and YH; Writing—review and editing, WC. All authors read and approved the final manuscript.

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