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A Research Method for Early Warning and Response to Security Risks of Large Sporting Events Based on Artificial Intelligence Deep Learning Networks

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SUMMARY: *Large-scale sports events are characterized by multiple factors, multiple levels and multiple targets, which imply large-scale security problems while generating exciting sports content. With reference to the results of two rounds of expert consultation, this paper proposes an early warning system for security risk of large-scale sports events structured by 9 secondary indicators and 27 tertiary indicators in three dimensions: pre-game preparation risk, game-time operation risk and post-game recovery risk. The principal component analysis is chosen as the calculation method of the principal component values of the experimental samples, and combined with the improved BP neural network algorithm, it forms the construction scheme of the risk warning model. The comprehensive weights of the early warning system indicators are calculated by integrating the Analytic Hierarchy Process (AHP) and the entropy weight method. Among them, the comprehensive weight values of the four secondary indicators, namely "venue security prevention risk", "venue operation plan risk", "venue financial preparation risk" and "venue post-event financial risk", are greater than 0.100, which are the key focus directions for security risk prevention in large-scale sports events. The constructed security risk warning model for large-scale sports events has an overall output accuracy of 91.07%, which can accurately output the security risk situation of sports events. This paper suggests that the preparation and organization of large-scale sports events should be supported by the early warning model, combined with the venues where the events are held, to formulate adequate security prevention and operation plans, prepare sufficient financial resources, and strategically respond to the security risks that may arise in sports events.*

KEYWORDS: *principal component analysis; security risk early warning system; improved BP neural network; large-scale sports events*

1 Introduction

In recent years, as a very important part of the sports industry, large-scale sports events have been frequently held in various countries, which has played a positive role in promoting the further development of the global sports industry [1]. As a large-scale activity providing products and services, the economic benefits and influence of sports events have been widely noticed. Compared with general sports events, large-scale sports events show their own unique nature, with strong competition, large scale, high standards, difficult to organize and great influence and other characteristics, which also causes large-scale sports events in the actual process of holding a strong complexity and uncontrollability, which is accompanied by a certain

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degree of event risk [2-6]. Usually, when the scale of the sports event is bigger, the risk of the sports event is often higher, the event risk will not only affect the life and health safety of the personnel, but also bring greater losses to the event organizer, so strengthen the management of large-scale sports event risk, to ensure that the safety of the sports event, the stability of the implementation of an important role [7-11].

Event risk management is mainly based on security risk management, with special attention paid to the risk management of participants' life safety, which is due to the fact that when measuring and evaluating the effect of organizing large-scale sports events, the presence or absence of athletes' life safety events and major collective security events are usually regarded as an important criterion for measurement [12-16]. When organizing large-scale sports events, the security risk management model is often based on patrol and monitoring assistance, however, this model has multiple problems, such as slow response time, easy to miss subtle key risks, data silos, and difficult to capture real-time risks and real-time warnings [17-20]. In order to further improve the life and health safety of participants, it is necessary to provide early warning of security risks and target response strategies. For example, literature [21] suggests embedding a multi-center bilateral interaction mechanism for the information management system of sports events activities in Jiangsu Province, promoting multi-body collaboration in sports events with the help of blockchain and cloud computing technology, and requiring the construction of a full closed-loop supervision process with real-time analysis and intelligent response, so as to improve the security of the event. Literature [22] uses large-scale sports event scenario analysis and drone camera monitoring to make dynamic decisions on the command and control center, and helps to improve the event risk situational awareness ability, while proposing effective response to potential risk decisions. Literature [23] analyzes security issues and measures in professional sports venues and suggests strategies to increase security investments, such as staff training, multiple communication platforms, improved security policy systems, and analytical tools, emphasizing the need to make full use of technology to provide solutions to security issues.

With the deep development of computer technology, artificial intelligence deep learning network technology as an advanced digital technology, which simulates the connection between neurons, realizes the intelligent analysis and processing of a large amount of data, and performs tasks such as pattern recognition, classification, and prediction [24, 25]. The core of Deep Learning (DL) is artificial neural network, which is made of a large number of artificial neurons interconnected with each other, and is able to mimic the machine learning method of the structure and function of the human brain neural network, which provides support for the early warning of the risk of safety accidents and response decision-making. Literature [26] combines particle swarm optimization algorithm and event risk prediction based on radial basis function neural network to develop a sports event risk early warning strategy, which is used to prevent and control the event risk and reduce the loss. Literature [27] assessed the risk of large sporting events from climate factors, event management, and natural disaster risk indicators by back propagation neural network, and ranked and constructed early warning models for these risk factors. Literature [28] used AI technology to construct cyber-physical systems in international sports stadiums from the perspective of cyber-attacks and hostile behaviors suffered by the network for predicting anomalous cyber-behaviors and assisting in monitoring and security warnings. Literature [29] formulated intelligent identification and early warning of marathon style public safety risks through all-round monitoring of the event by drones, and embedded a drone-based command platform to realize risk management for the whole marathon. Literature [30] utilized sensor-based IoT devices to obtain weather, building, and participant data, introduced deep neural networks to assess and predict outdoor sports risks, and proposed corresponding safety control strategies. Literature [31] developed a risk management assessment method for outdoor sports safety based on an embedded system, and the system has an encrypted outdoor sports safety database, predicts risks using real-time collected data, and outputs corresponding warning messages. Literature [32] proposed an AI-based predictive fire alarm and evacuation model by collecting fire-related data such as temperature and humidity through multi-sensors deployed in sports stadiums, which also helps to improve the orderly flow of crowds. Literature [33] develops a real-time prediction model for DL risk space based on surveillance camera images in the risk level classification of mass events, such as crowd stampede, for detecting and predicting the risk of crowd stampede in large gatherings.

In this paper, we first calculate the degree of expert authority and the coefficient of variation of expert consultation, and launch two rounds of expert consultation on the security risk warning system for large sporting events. The final security risk warning system for large-scale sporting events is established by combining the modification suggestions of experts and listing the specific contents of the indicators. Then the principal component analysis method and the improved BP network algorithm are used to design the security risk early warning model. Subsequently, the hierarchical analysis method and entropy weighting method are used to calculate the comprehensive weights of the indicators of the early warning system, and analyze the prevention focus and response path of the security risk in large-scale sports events based on the weight values. Finally, test samples are selected, and the sample set is established through principal component analysis to determine the structure of the early warning network. After completing the training of the network, the network is applied to predict the security risk of the samples and calculate its overall accuracy to verify the feasibility of the combination of principal component analysis and improved BP network algorithm.

2 Establishment of an early warning system for security risks at major sporting events

2.1 Methodology for expert advice

2.1.1 Degree of expert authority

The reliability of the results of the assessment depends mainly on the degree of authority of the expert, so the degree of authority of the expert in assessing the problem needs to be analyzed before the results are assessed. The expert's familiarity with the problem and the basis on which the expert judges the program are two factors that affect the expert's degree of authority.

Generally speaking, the experts' familiarity with the problem is divided into six levels: very unfamiliar, less familiar, average, more familiar, familiar and very familiar. And the basis of expert judgment includes four aspects such as practical experience, theoretical analysis, peer understanding or intuition. The size of the judgment coefficient indicates that the basis of judgment has a different degree of influence on the experts, and when the sum of the judgment coefficients is 1, 0.8 and 0.6, respectively, it indicates that the degree of influence of the basis of judgment on the experts corresponds to very large, medium and small, respectively.

The expert's familiarity with the indicator (C_s) is divided into six levels: very unfamiliar, less familiar, average, more familiar, familiar, very familiar, corresponding to C_s values of 0.0, 0.1, 0.3, 0.5, 0.7, 0.9 in that order.

The degree of expert authority is the arithmetic average of the coefficient of expert familiarity and the coefficient of expert judgment, and the calculation formula can be expressed as formula (1):

$$C_r = \frac{C_s + C_a}{2} \tag{1}$$

where C_r is the degree of expert authority, C_s is the degree of familiarity, and C_a is the judgment coefficient.

According to the formula for calculating the degree of authority, the degree of authority of the experts on the security risk early warning system for large-scale sports events in this paper is calculated as shown in Table 1 for the three first-level assessment contents of (X) pre-game preparation stage, (Y) game operation stage and (Z) post-game restoration stage, and the average value of the degree of authority of the experts for the three first-level assessment contents is 0.82, 0.82 and 0.85 > 0.8 respectively, which indicates that the consulting experts have a higher degree of authority.

Table 1: The degree of expert authority

Index	C_S	C_a	C_r
(X)	0.83	0.81	0.82
(Y)	0.79	0.85	0.82
(Z)	0.86	0.84	0.85

2.1.2 Coefficient of variation for expert advice

The coefficient of variation, denoted as CV, is the ratio of the standard deviation to the mean, and is a statistical measure of the degree of variability of each observation in the data. The function of CV is able to reflect the degree of dispersion on the unit mean, commonly used in the comparison of the degree of dispersion of the two overall means are not equal, of course, the two overall means are equal, then compare the standard deviation coefficient with the comparison of the standard deviation is equivalent to the calculation of CV as in equation (2)-(3):

$$M_j = \frac{1}{n}\sum_{i=1}^{n} X_{ij} \tag{2}$$

$$\sigma_j = \sqrt{\frac{1}{n-1}\sum_{i=1}^{n}(X_{ij} - M_j)^2} \tag{3}$$

Then the coefficient of variation is calculated as in equation (4):

$$CV_j = \frac{\sigma_j}{M_j} \tag{4}$$

where X_{ij} denotes the j th comment of the i th expert. The smaller the value of the coefficient of variation, the less dispersed the expert evaluation results are, and it is generally believed that $CV \geq 0.25$ is considered to be insufficiently coordinated for this indicator.

2.2 Revision and establishment of the indicator system

2.2.1 Results of the first round of expert consultation

In the questionnaire of the first round of expert consultation, participating experts were asked to evaluate each assessment indicator from the perspectives of importance and operability, and the evaluation of the indicators was divided into five grades: very good, good, average, poor, and very poor, with the values of 9, 7, 5, 3, and 1, respectively. The data of the first round of expert consultation were recorded and analyzed by using Excle Statistical Software, and the importance and operability of the indicators of all levels were calculated separately. The mean, standard deviation and coefficient of variation of the indicators were calculated separately. The arithmetic mean of the indicators represents the degree of concentration of experts' opinions, and the larger its value, the higher the importance of the indicator and the better its operability. The coefficient of variation mainly indicates the degree of coordination of all experts' judgmental opinions on an indicator, and obviously a small coefficient of variation corresponds to a high degree of coordination among experts on the indicator. The statistical results of the first round of expert consultation are shown in Table 2.

Table 2: The statistical results of the first round of expert consultation

Index	Importance			Maneuverability		
	Arithmetic mean	SD	CV	Arithmetic mean	SD	CV
(X)	7.9	0.5	0.16	7.7	0.76	0.16
(Y)	7.5	0.59	0.2	8.4	1.09	0.17
(Z)	7.9	0.63	0.11	7.1	0.8	0.14
(X1)	7.1	1.46	0.09	8.8	0.89	0.14
(X2)	8.9	1.12	0.19	7.1	1.37	**0.25**
(X3)	7.6	0.82	0.1	7.5	1.22	0.10
(X4)	8.6	0.63	0.19	7.6	1.62	0.15
(Y1)	8.0	0.65	0.09	7.6	1.28	0.15
(Y2)	8.6	0.25	0.1	8.2	1.67	0.15
(Y3)	8.4	0.51	0.09	8.9	0.98	0.14
(Z1)	7.1	0.53	0.17	7.1	0.92	0.15
(Z2)	8.2	0.45	0.08	8.5	1.31	0.09
(X11)	8.5	0.22	0.15	8.4	1.45	0.15
(X12)	8.1	1.38	0.2	8.4	1.39	0.10
(X13)	8.8	1.23	0.06	7.4	1.58	0.11
(X21)	7.2	1.29	0.15	8.4	1.65	0.18
(X22)	8.7	0.62	0.19	7.1	1.07	0.21
(X23)	8.6	0.29	0.24	7.7	1.65	**0.25**
(X24)	8.9	0.38	0.16	6.1	0.74	**0.28**
(X31)	8.3	0.73	0.14	8.1	1.51	0.16
(X32)	7.2	0.44	0.08	8.2	0.83	0.12
(X41)	8.0	0.29	0.16	6.5	1.07	**0.26**
(X42)	7.5	1.03	0.19	8.7	1.11	0.17
(X43)	8.2	0.65	0.13	8.2	0.95	0.20
(X44)	7.7	0.43	0.2	7.8	1.25	0.11
(Y11)	8.7	0.35	0.11	7.5	0.71	0.13
(Y12)	8.5	0.46	0.14	7.5	1.45	0.12
(Y21)	7.6	0.75	0.15	8.9	1.4	0.10
(Y22)	8.3	1.12	0.17	7.3	1.2	0.12
(Y23)	7.4	1.48	0.14	8.1	0.99	0.19
(Y24)	7.4	0.98	0.08	7.8	1.68	0.11
(Y31)	7.3	0.59	0.05	7.2	0.98	0.12
(Y32)	8.9	1.04	0.11	8.1	1.11	0.09
(Y33)	8.7	0.85	0.1	8.7	1.09	0.07
(Z11)	7.2	1.39	0.13	8.4	1.66	0.08
(Z12)	8.1	0.6	0.06	7.3	1.12	0.12
(Z21)	7.1	0.45	0.19	8.5	1.39	0.04
(Z22)	8.8	0.22	0.17	7.8	1.67	0.13

Among them, there are: secondary indicator (X2) the risk of preparing human resources for the venue, tertiary indicator (X23) the risk of personnel training, (X24) the risk of personnel evaluation and incentives and (X41) the risk of the venue's spatial layout, a total of four indicators of operability coefficient of variation ≥ 0.25. On the basis of fully weighing the modifications proposed by the experts, certain modifications were made to the indicator system of the first round of evaluation, and the second round of expert consultation questionnaires was made. The specific modifications are as follows:

(1) A new tertiary indicator (X25) Venue Team Building Risk has been added to the secondary indicator (X2) Venue Human Resources Preparation Risk.

(2) Tertiary indicator (X23) personnel training risk is revised to (X23) personnel training and rehearsal risk, and tertiary indicator (X24) personnel appointment risk is revised to (X24) personnel evaluation and motivation risk.

(3) Tertiary indicator (X41) venue space layout risk was originally under secondary indicator (X4) venue physical preparation risk, and is now under secondary indicator (X1) venue operation plan risk.

2.2.2 Results of the second round of expert consultation

Summarize the results of the first round of expert consultation, make the questionnaire for the second round of expert consultation, and at the same time feedback the statistical results to the experts who have participated in the first round of expert consultation, and ask the experts to evaluate the assessment indicators from the aspects of importance and operability, and at the same time obtain the degree of familiarity of the experts with each indicator. Excle statistical software was also used to calculate the mean, standard deviation and coefficient of variation of the assessment indicators in terms of importance and operability, and the statistical results of the second round of expert consultation are shown in Table 3.

Table 3: The statistical results of the second round of expert consultation

Index	Importance			Maneuverability		
	Arithmetic mean	SD	CV	Arithmetic mean	SD	CV
(X)	7.8	0.84	0.15	8.8	1.03	0.07
(Y)	9.3	1.14	0.07	8.4	0.83	0.13
(Z)	8.9	1.45	0.09	8.9	1.22	0.24
(X1)	8.6	0.94	0.13	9.1	0.87	0.17
(X2)	9.2	0.58	0.14	7.6	1.24	0.14
(X3)	8.7	1.14	0.24	9.1	1.45	0.16
(X4)	8.7	0.95	0.24	9.1	1.46	0.20
(Y1)	9.2	0.74	0.18	7.8	0.93	0.23
(Y2)	8.6	0.68	0.23	9.3	0.68	0.04
(Y3)	7.3	1.44	0.05	9.3	1.27	0.08
(Z1)	7.6	1.18	0.19	8.8	1.12	0.15
(Z2)	7.7	1.27	0.14	7.9	0.81	0.11
(X11)	7.8	0.54	0.17	8.2	1.07	0.04
(X12)	8.3	1.16	0.12	9.1	0.65	0.17
(X13)	7.1	0.87	0.11	8.3	1.29	0.16
(X41)	9.5	1.16	0.24	8.1	0.71	0.11
(X21)	8.7	1.08	0.20	7.6	1.59	0.11
(X22)	9.3	1.12	0.08	9.4	0.95	0.18
(X23)	8.2	0.81	0.12	7.8	0.63	0.09
(X24)	8.8	0.62	0.21	8.9	0.79	0.03
(X25)	8.2	1.48	0.14	9.3	0.78	0.12
(X31)	9.3	0.85	0.05	8.4	0.62	0.07
(X32)	8.7	0.81	0.24	9.1	1.41	0.13
(X42)	8.4	0.97	0.21	8.8	0.58	0.12
(X43)	7.1	0.73	0.16	8.4	1.46	0.24
(X44)	8.7	0.86	0.22	8.6	0.82	0.22
(Y11)	7.2	1.15	0.05	7.6	1.03	0.06
(Y12)	9.1	0.65	0.24	8.7	1.22	0.19
(Y21)	8.5	0.65	0.14	8.5	0.95	0.12
(Y22)	8.1	1.04	0.22	7.9	1.07	0.11
(Y23)	8.9	1.08	0.06	8.3	1.33	0.16
(Y24)	8.5	0.51	0.06	8.6	0.82	0.06
(Y31)	8.5	1.43	0.14	8.6	0.84	0.16
(Y32)	8.1	1.41	0.08	8.7	1.08	0.08
(Y33)	8.6	0.83	0.17	8.4	1.12	0.18
(Z11)	9.1	0.73	0.06	9.2	0.94	0.19
(Z12)	9.2	0.53	0.11	8.5	1.54	0.18
(Z21)	8.9	1.32	0.08	8.9	1.03	0.11
(Z22)	8.9	1.49	0.16	8.3	0.91	0.23

After mathematical and statistical analysis, the importance and operability expert opinion coordination coefficient of each indicator of the revised security risk early warning system for large-scale sports events is close to 0.5, and the P-value is <0.5 by the x2 test, indicating that this round of expert opinion is coordinated and statistically significant. Accordingly, an early warning system for security risks of major sports events was established, which contains three primary indicators (X) pre-event preparation risk, (Y) operation risk and (Z) post-event recovery risk, nine secondary indicators and 27 tertiary indicators, as shown in Table 4.

Table 4: Security risk assessment system for large-scale sports events

Primary index	Secondary index	Three-level index
(X)Pre-competition preparation risks	(X1)Risks of venue operation plans	(X11) Risks in formulating customer group service plans
		(X12) Risks in formulating security plans and emergency response plans
		(X13) Risks in the formulation of venue operation tasks and procedures
		(X41) Risk of venue spatial layout
	(X2)Risk of venue manpower preparation	(X21) Risk of human resource planning
		(X22) Risk of personnel recruitment and selection
		(X23) Risk of personnel training and drills
		(X24) Risk of personnel assessment and motivation
		(X25) Risk of venue team building
	(X3)Risk of financial preparation for the venue	(X31) Risk of venue operation financial budget
		(X32) Risk of venue operation financial control
	(X4)Risk of venue material preparation	(X42) Risks of temporary facility construction in the venue
		(X43) Risks of permanent building facility management in the venue
		(X44) Risks of material supply in the venue
(Y) Operational risks during the competition	(Y1)Venue security prevention risks	(Y11) Risks of security and protection
		(Y12) Risks of traffic, fire and evacuation
	(Y2)Risks of competition services in venues	(Y21) Risks of audience services
		(Y22) Risks of medical and health services
		(Y23) Risks of technical services
		(Y24) Other service risks
	(Y3)Risks in venue logistics support	(Y31) Venue facility management risks
		(Y32) Venue Environmental Maintenance Risks
		(Y33) Venue Property Supply Risks
(Z) Post-match recovery risk	(Z1)Risk of evacuating people and objects after the	(Z11) Venue personnel Evacuation Risks
		(Z12) Venue building Facility Damage Risks
	(Z2)Post-event financial risks of the venue	(Z21) Venue asset loss risks
		(Z22) Venue Financial overspending risks

3 Methodology for constructing security risk early warning models

3.1 Principal component analysis

Due to the relatively excessive number of indicators in the security risk early warning system for large sporting events, it is not only complicated to analyze, but also easy to lead to high correlation or multiple covariance problems among the indicators, which affects the accuracy of the conclusions. Therefore, in order to overcome this problem, this paper firstly carries out dimensionality reduction through the method of principal component analysis.

Principal component analysis is a mathematical approach to dealing with dimensionality reduction. The idea of this method is: try to take the original numerous indicators with certain correlation (such as P ones), extract some of them (such as m ones, $m \leq p$) mutually independent principal components, and recombine them into a new set of mutually unrelated composite indicators to replace the original indicators. If the cumulative contribution rate of the extracted principal components reaches more than 80%, it can be considered that the extracted indicators can maximize the retention of the information of the original indicators. The specific steps of principal component analysis are as follows.

3.1.1 Standardization of raw data

There are n sports event venues and each sample is described by p security risk indicators $x_1, x_2, \cdots, x_p$ as in equation (5):

$$X = \begin{pmatrix} x_{11} x_{12} \cdots x_{1p} \\ x_{21} x_{22} \cdots x_{2p} \\ \cdots \\ x_{n1} x_{n2} \cdots x_{np} \end{pmatrix} = \left(X_1, X_2, \cdots X_p \right) \tag{5}$$

where $X_i = \left(x_{1i}, x_{2i}, \cdots x_{ni} \right)$, and p is the number of security risk indicators selected by the model.

When conducting principal component analysis, the first step is to calculate the covariance matrix of the evaluation indicators, in order to reduce the influence of the evaluation indicators' scale and order of magnitude on the covariance, this paper first standardizes the original indicators using the Z-score formula. Here the standardized indicator matrix is set as V . The standardized treatment is as equation (6):

$$v_{ij} = \frac{x_{ij} - \overline{x}_j}{S_j} \tag{6}$$

3.1.2 Calculation of the correlation coefficient matrix (covariance matrix)

After normalization, the covariance matrix of the security risk indicator is equal to the matrix of correlation coefficients $R\left(R = \left(r_{ij}\right)\right)$, and r_{ij} is computed as equation (7):

$$r_{ij} = \frac{S_{ij}}{\sqrt{S_{ij}}\sqrt{S_{jj}}} \tag{7}$$

where $S_{ij} = \frac{1}{n-1}\sum_{i=1}^{n}\left(x_{ij} - \bar{x}_i\right)\left(x_{ij} - \bar{x}_j\right)$

It can be seen that R is a real symmetric matrix (i.e., $r_{ij} = r_{ji}$), so it is only necessary to compute its upper or lower triangular elements.

3.1.3 Computing eigenvalues and eigenvectors

Solving the eigenequation $\left|\ddot{e}I - R\right| = 0$ by Jacobi's method yields the eigenvalues $\ddot{e}\left(i = 1, 2, \cdots, p\right)$, and since R is a positive definite matrix, the eigenvalues $\ddot{e}$ are all positive in order of their magnitude, i.e. $\ddot{e}_1 \geq \ddot{e}_2 \geq \cdots \geq \lambda_1 \geq \lambda_p$, the eigenvalue is the variance of the principal components, and its magnitude reflects the role of each principal component in describing the object being evaluated. The eigenvector matrix U can be obtained by the equation $\left|R - \ddot{e}_i I\right| U = 0$.

Let $F = U^T V$, i.e., equation (8):

$$FF^T \doteq \begin{pmatrix} \lambda_1 & & & 0 \\ & \bullet & & \\ & & \bullet & \\ & & & \bullet \\ 0 & & & \lambda_p \end{pmatrix} \tag{8}$$

The F is known as the factor score coefficient matrix.

3.1.4 Calculating principal component contributions and cumulative contributions

The variance contribution of the m st principal component Y_m is equation (9):

$$a_m = \lambda_i \Big/ \sum_{i=1}^{p} \lambda_i \tag{9}$$

The cumulative variance contribution of the first m principal components $Y_1, Y_2, \cdots, Y_m$ is given in equation (10):

$$a(m) = \sum_{j=1}^{m} \lambda_j \Big/ \sum_{i=1}^{p} \lambda_i \tag{10}$$

The variance contribution ratio a_m of Y_m denotes the share of the variance of this principal component in the total variance of the original indicator, i.e., the amount of information extracted from the original p indicator by the m principal component. Therefore, the larger the cumulative variance contribution ratio $a(m)$ of the first m principal components $Y_1, Y_2, \cdots, Y_m$, the more information the first m principal components contain.

3.1.5 Selection of the number of principal components

The significance of the principal component analysis method lies in the fact that, while maximizing the retention of the original security risk indicator information, a large number of original security risk indicators are reduced to a small number of composite indicators, which not only simplifies the testing process, but also ensures the reliability of the conclusion information. Therefore, in the process of principal component analysis, the goal is to obtain as few principal components as possible and a larger variance contribution rate, so as to realize that a smaller number of principal components represents a sufficient amount of information on the original security risk indicators.

There are generally two requirements when determining the number of principal components, namely, the requirement that the cumulative variance contribution rate of the first m principal components is not less than 80% or the requirement that the eigenroot is greater than 1. In this paper, we will follow the former requirement. Since the extracted principal components are sorted according to the size of the eigenvalues, when determining the number of principal components m, it is sufficient to extract only the first m principal components that meet the requirements.

The selected m principal components divide the matrix U into two parts: $U_{p\times p}=\left(U^{(1)}_{p\times m},U^{2}_{p\times(p-m)}\right)$, and there is Equation (11):

$$V=UF=\left(U^{(1)},U^{(2)}\right)\times\left(F^{(1)},F^{(2)}\right)^{T}=U^{(1)}_{p\times m}F^{(1)}_{m\times n}+U^{(2)}_{p\times(p-m)}F^{(2)}_{(p-m)\times n} \tag{11}$$

where $U^{(1)}F^{(1)}$ is the information explained by the main component and $U^{(2)}F^{(2)}$ is the residual information. Based on the matrix of factor score coefficients, the security risk indicator V_i can be expressed as equation (12):

$$V_i=U_{i1}F_1+U_{i2}F_2+\cdots+U_{im}F_m \tag{12}$$

3.2 Improved BP network algorithm

The standard most rapid descent method often has the disadvantage of slow convergence in practical applications. In response to the shortcomings of the standard BP algorithm, several improvements of the standard BP method have emerged, such as the momentum BP method and the LM algorithm.

(1) Momentum BP method

Momentum BP method is to introduce the momentum factor $mc\left(0<mc<1\right)$ in the weight update stage of the standard BP algorithm, so that the weight correction has a certain inertia see equation (13):

$$\Delta\omega(n)=-\eta(1-mc)\nabla e(n)+mc\Delta\omega(n-1) \tag{13}$$

Compared to the standard most rapid descent BP method, the above equation has an additional factorization $mc\Delta\omega(n-1)$ when updating the weights. It indicates that the direction and magnitude of the update of the current weights are not only related to the gradient obtained from the current calculation, but also related to the direction and magnitude of the previous update. The addition of this factorization gives the update of the weights a certain inertia and a certain ability to resist oscillations and accelerate convergence. In specific applications, the momentum factor is generally taken as 0.1-0.9.

(2) BP algorithm with variable learning rate

In the standard fastest descent BP method, the learning rate is a constant, so the choice of the learning rate has a huge impact on the performance. If the learning rate is too small, the convergence speed is slow; if the learning rate is too large, it is easy to oscillate. For different problems, the learning rate can only be roughly determined empirically. In fact, in different stages of training, the value of the learning rate is different, such as the direction of a more single region, you can choose a larger learning rate, in the vicinity of the “valley”, you should choose a smaller learning rate. If we can adaptively determine the different situations and adjust the value of learning rate, it will improve the performance and stability of the algorithm.

The BP algorithm with variable learning rate (VLBP) is judged by observing the increase or decrease of the error. When the error tends to the target in a decreasing manner, it means that the correction is in the right direction and the learning rate can be increased; when the error increases beyond a certain range, it means that the previous correction was performed incorrectly and the step size should be reduced and the previous correction process should be undone. The increase or decrease of the learning rate is realized by multiplying an increase/decrease factor see equation (14):

$$\eta(n+1) = \begin{cases} k_{inc}\eta(n) & e(n+1) < e(n) \\ k_{dec}\eta(n) & e(n+1) > e(n) \end{cases} \tag{14}$$

(3) LM algorithm

The LM algorithm, is designed to avoid the calculation of the Hessian matrix when correcting the rate.The Hessian matrix is see equation (15):

$$H = \begin{bmatrix} \dfrac{\partial^2 f}{\partial x^2} & \dfrac{\partial^2 f}{\partial x \partial y} \\ \dfrac{\partial^2 f}{\partial y \partial x} & \dfrac{\partial^2 f}{\partial y^2} \end{bmatrix} \tag{15}$$

When the error performance function has the form of sum-of-squares error, the Hessian matrix can be approximated as see equation (16):

$$H = J^T J \tag{16}$$

The gradient can be expressed as see equation (17):

$$g = J^T e \tag{17}$$

J is the Jacobi matrix containing the first-order derivatives of the error performance function with respect to the network weights.The LM algorithm corrects the network weights according to the following equation as Eq. (18):

$$\omega(n+1) = \omega(n) - [J^T J + \mu I]^{-1} J^T e \tag{18}$$

When $\mu = 0$, the LM algorithm degenerates to Newton's method; when μ is large, the above equation is equivalent to the gradient descent method with a smaller step size. Since the Jacobi matrix is easier to compute than the Hessian matrix, it is very fast.

4 Establishment of an early warning model for security risks at major sporting events

4.1 Assignment of weights to and analysis of indicators of the early warning system

Using the hierarchical analysis method combined with entropy weight method to calculate the weights of indicators at all levels of the security risk early warning system for large-scale sports events, the subjective weights of the indicators of the early warning system (W_j), the objective weights (H_j) and the comprehensive weights (D_j) are shown in Table 5. On the whole, the weights calculated by hierarchical analysis method and entropy weighting method differ greatly in a certain index, and a good combination of subjective and objective weights of the indexes can be realized by synthesizing the two.

Table 5: Subjective weight, objective weight and comprehensive weight

Index	W_j	H_j	D_j
(X)	0.166	0.327	0.306
(Y)	0.374	0.509	0.463
(Z)	0.537	0.164	0.231
(X1)	0.172	0.197	0.145
(X2)	0.163	0.061	0.075
(X3)	0.019	0.156	0.137
(X4)	0.044	0.094	0.086
(Y1)	0.208	0.192	0.172
(Y2)	0.123	0.065	0.089
(Y3)	0.224	0.086	0.093
(Z1)	0.133	0.063	0.098
(Z2)	0.164	0.086	0.105
(X11)	0.258	0.037	0.031
(X12)	0.124	0.034	0.029
(X13)	0.389	0.053	0.057
(X41)	0.229	0.035	0.029
(X21)	0.212	0.034	0.039
(X22)	0.135	0.025	0.031
(X23)	0.218	0.034	0.027
(X24)	0.179	0.022	0.026
(X25)	0.256	0.028	0.029
(X31)	0.368	0.053	0.055
(X32)	0.632	0.051	0.056
(X42)	0.347	0.049	0.052
(X43)	0.315	0.035	0.027
(X44)	0.338	0.038	0.021
(Y11)	0.362	0.054	0.069
(Y12)	0.638	0.051	0.065
(Y21)	0.145	0.026	0.029
(Y22)	0.291	0.022	0.019
(Y23)	0.185	0.021	0.023
(Y24)	0.379	0.032	0.022
(Y31)	0.183	0.027	0.031
(Y32)	0.338	0.028	0.029
(Y33)	0.479	0.023	0.025
(Z11)	0.435	0.058	0.058
(Z12)	0.565	0.043	0.049
(Z21)	0.259	0.029	0.028
(Z22)	0.741	0.058	0.044

In addition, from the comprehensive weight value in the first level dimension, “(Y) Risk of operation during the game” dimension is the focus of the security risk warning and response of large-scale sports events, and its comprehensive weight value is 0.463. This dimension is centered on the indicator “(Y1) Risks to the security of the venue”, which has a combined weight of 0.172. In addition, among the secondary indicators, there are three items that need to be closely watched: "(X1) Venue Operation Plan Risk", "(X3) Venue Financial Preparation Risk", and "(Z2) Venue post-event Financial Risk". Their weight values are all 0.100 or above, namely 0.145, 0.137, and 0.105. Among the three-level indexes, there are two contents belonging to the second-level index (Y1) venue security risk prevention (Y11) security risk (0.069), (Y12) transportation and fire evacuation risk (0.065) is the most important, the comprehensive weight value are up to 0.060 above.

Accordingly, this paper argues that during the preparation and implementation of large-scale sports events, the prevention of security risks of large-scale events should be addressed from the following aspects: the venue security level needs to be implemented through the implementation of a number of security programs tailored to suit the local conditions, monitoring and safeguarding the progress of the event security, prepare adequate and sufficient security contingency plans, and to maintain a safe atmosphere in the arena. In the venue operation plan level, around the customer service, security and emergency planning, operational tasks and procedures to develop, space layout of a total of four levels, to develop a detailed venue operation plan program. At the level of venue financial resources, not only do we need to prepare financial resources to meet the needs of pre-game preparation, game time, and post-game finishing, but we also need to pay special attention to post-game financial settlements to avoid loss of assets.

4.2 Early Warning of Security Risks in Sporting Events Based on BP Neural Networks

4.2.1 Sample Selection and Principal Component Analysis

A total of 500 major sports events (1-500) were selected as the study sample and a total of 25 major sports events (1-100) were selected as the test sample, and the security risk level of the sample was assessed by the security risk early warning system for major sports events, as shown in Table 6.The risk level was classified into the following five grades: very weak, weak, average, strong, and strong, which corresponded to the numerical values of 5, 4, 3, 2, and 1 in that order. 100 events were tested, of which 69 had an overall security risk score of 3, which was in the average grade, and each had 11 events in the weak and strong grades. Of the 100 samples tested, 69 events had an overall security risk rating of 3, which is average, 11 events had weak or strong overall security risk, 7 events had weak security risk, and 2 events had strong security risk.

Table 6: The original data and grade of the sample

Index	Learning sample							Test sample						
	1	2	3	…	498	499	500	1	2	3	…	98	99	100
(X11)	4	4	5	…	4	5	4	2	2	5	…	5	4	1
(X12)	3	4	4	…	5	5	4	2	2	3	…	4	3	2
(X13)	3	4	3	…	5	3	3	1	4	3	…	5	4	1
(X41)	4	5	5	…	4	4	4	2	4	3	…	4	2	3
(X21)	2	3	4	…	5	4	5	2	3	4	…	3	3	2
(X22)	3	4	4	…	5	5	5	1	2	3	…	3	3	3
(X23)	4	4	5	…	5	5	3	1	4	3	…	3	4	3
(X24)	1	4	4	…	4	4	3	2	4	4	…	4	5	2
(X25)	3	4	4	…	5	3	4	2	4	3	…	2	5	2
(X31)	3	4	3	…	5	4	5	1	2	3	…	2	1	2
(X32)	3	3	4	…	4	5	4	2	3	4	…	2	2	2
(X42)	2	5	4	…	5	3	5	1	4	3	…	3	4	4
(X43)	3	3	4	…	5	3	3	1	2	5	…	5	4	3
(X44)	4	4	4	…	4	3	4	1	2	3	…	3	1	1
(Y11)	3	4	4	…	3	4	4	2	4	3	…	4	3	4
(Y12)	4	4	4	…	5	4	4	1	2	3	…	3	3	1
(Y21)	2	3	4	…	4	3	5	2	2	3	…	3	1	4
(Y22)	1	3	3	…	4	4	4	1	2	4	…	4	5	2
(Y23)	2	4	3	…	5	4	4	1	5	4	…	5	5	3
(Y24)	2	3	4	…	3	4	3	1	2	4	…	3	2	3
(Y31)	3	4	3	…	5	4	4	1	3	3	…	5	2	1
(Y32)	3	3	4	…	4	4	3	2	3	5	…	3	2	3
(Y33)	1	5	5	…	5	5	5	1	4	5	…	3	4	3
(Z11)	3	4	5	…	4	5	5	2	4	3	…	4	3	2
(Z12)	2	4	3	…	5	5	4	2	3	3	…	5	3	2
(Z21)	3	3	5	…	5	4	3	1	2	3	…	3	2	1
(Z22)	2	4	3	…	5	4	3	1	5	2	…	3	4	2
Level	3	4	4	…	5	4	4	1	3	3	…	4	3	2

Using the principal component analysis method to analyze the original data and survey data in Table 6, the cumulative contribution rate of the first six factors obtained from the extraction is more than 85.46%, which means that these six principal components are chosen to be able to explain more than 85.46% of the original data information. Therefore, network training was performed on these 6 data, and the value of each principal component was calculated to form the sample set shown in Table 7.

Table 7: Principal component of the sample

Sample	Serial number	Principal component						Level
		1	2	3	4	5	6	
Learning Sample	1	0.85	0.34	0.69	-0.35	-0.35	0.66	3
	2	-0.71	1.54	1.27	-0.54	-1.42	1.35	4
	3	0.02	-0.68	1.09	0.35	-0.52	0.18	4
	…	…	…	…	…	…	…	…
	498	-0.47	0.89	0.51	-0.06	-0.02	0.98	5
	499	-0.44	0.12	0.15	0.63	0.14	-0.58	4
	500	-0.28	0.28	0.58	-0.16	0.98	-0.52	4
Test Sample	1	-0.22	-0.29	-0.2	0.54	0.28	-0.97	1
	2	-0.37	-0.81	0.01	0.23	-0.23	0.25	3
	3	-0.99	-0.86	0.12	0.05	0.23	-0.23	3
	…	…	…	…	…	…	…	…
	98	-0.12	-0.54	-1.17	1.04	0.86	-0.97	4
	99	-1.17	-0.12	-0.31	-0.37	0.22	1.51	3
	100	0.53	0.23	1.24	-0.75	0.25	0.55	2

4.2.2 Early warning network construction and validation

The structure of the improved BP neural network with three layers is selected, and since six principal components are extracted, the number of neurons in the input layer is set to 6, and the input data is the data calculated in Table 7. The number of neurons in the output layer is set to 5 according to the total evaluation conclusion set B={weak, weak, average, strong, very strong}, and the number of neurons in the hidden layer is set to 5 according to the empirical formula in Chapter 3, according to which, the neural network structure of this paper based on the improvement of BP neural network for the evaluation of the security risk of large-scale sports events is set to 6*5*5. After the training of this network, the resulting the error change curve of training based on the training samples is shown in Figure 1.

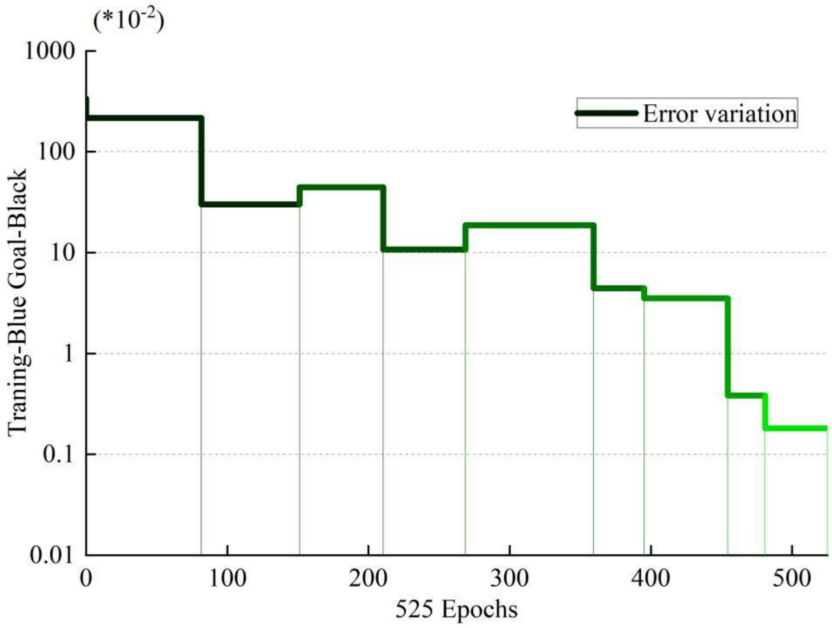

Figure 1: The error variation curve of training samples during training

After 525 trainings, the target error of the constructed network reached the demand (<0.01). At the end of training, the effectiveness of the security risk evaluation method for large sporting events based on improved BP neural network was verified by testing the test samples. The network outputs of the test samples are shown in Table 8.

Table 8: The output of the test sample network evaluation model

Num ber	Network output	Desired output	Num ber	Network output	Desired output	Num ber	Network output	Desired output
1	5	5	35	5	5	69	3	2
2	3	3	36	3	3	70	3	3
3	3	3	37	3	3	71	3	3
4	2	1	38	2	2	72	3	3
5	3	3	39	4	4	73	4	4
6	5	5	40	3	3	74	3	3
7	2	2	41	3	3	75	5	5
8	4	3	42	3	4	76	3	3
9	3	3	43	3	3	77	4	3
10	3	3	44	3	3	78	3	3
11	4	4	45	3	4	79	3	3
12	3	3	46	4	2	80	3	3
13	3	3	47	3	3	81	3	4
14	2	2	48	3	3	82	3	2
15	3	3	49	2	2	83	3	3
16	3	3	50	3	2	84	3	3
17	3	4	51	3	2	85	4	4
18	2	2	52	3	3	86	3	3
19	1	1	53	5	5	87	3	3
20	5	5	54	3	3	88	3	3
21	3	3	55	3	2	89	4	4
22	3	3	56	4	4	90	3	3
23	4	4	57	3	3	91	3	3
24	3	3	58	3	3	92	3	3
25	2	2	59	3	3	93	2	2
26	1	1	60	3	3	94	3	3
27	3	2	61	3	3	95	2	1
28	3	3	62	3	3	96	3	3
29	3	3	63	2	2	97	3	3
30	3	4	64	3	3	98	4	4
31	2	2	65	3	3	99	3	3
32	2	2	66	3	2	100	2	2
33	3	3	67	4	4			
34	3	3	68	3	3			

According to Table 8, it can be calculated that: Among the five security risk levels, the accuracy rates of online evaluations from very weak to very strong are 100.00%, 81.82%, 85.61%, 90.91%, and 100.00% respectively. Therefore, the comprehensive accuracy rate of online evaluations is 91.07%, which is relatively high. The effectiveness and feasibility of security risk early warning for large-scale sports events under the combination of principal component analysis and improved BP neural network have been verified.

5 Conclusion

This paper fully combines the expert advice, scientifically divides the security risk of large-scale sports events into three levels: pre-game preparation risk, game-time operation risk and post-game recovery risk, and establishes an early warning system for security risk of large-scale sports events with 9 secondary indicators and 27 tertiary indicators. Based on the fact that the comprehensive weight values of the four secondary indicators, namely "venue security prevention risk", "venue operation plan risk", "venue financial preparation risk" and "venue post-event financial risk", in this system are 0.100 or above, this paper proposes the prevention and response directions for security risks of large-scale sports events: (1) Reasonable and adequate security and event operation plans, (2) Sufficient financial resources for preparation and management.

Combining the principal component analysis method and the improved BP neural network, we constructed a 6*5*5 security risk warning model for large sporting events, and the overall accuracy of its security risk warning for large sporting events was 91.07%. The model is able to accurately identify and forecast the security situation of large-scale sports events, provide practical planning and improvement directions for the preparation and management of sports events, and construct a reliable security line of defense for large-scale sports events by using artificial intelligence deep learning network.

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