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Research Article

Application of Random Dynamic Grouping Simulation Algorithm in PE Teaching Evaluation

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The probability ranking conclusion is an extension of the absolute form evaluation conclusion. Firstly, the random simulation evaluation model is introduced; then, the general idea of converting the traditional evaluation method to the random simulation evaluation model is analyzed; on this basis, based on the rule of "further ensuring the stability of the ranking chain on the basis of increasing the possibility of the ranking chain," two methods of solving the probability ranking conclusion are given. Based on the rule of "further guaranteeing the stability of the ranking chain on the basis of improving the likelihood of the ranking chain," two methods are given to solve the likelihood conclusion. This paper argues that this absolute form of conclusion hinders the approximation of the theory to the essence of the actual problem and is an important reason for the problem of "non-consistency of multi-evaluation conclusions." To address this problem, a stochastic simulation-based comprehensive evaluation solution algorithm based on the idea of "Monte Carlo simulation" is proposed, and the corresponding ranking method is investigated, which is characterized by generating evaluation conclusions with probability (reliability) information, and thus has more advantages than the absolute conclusion form in terms of problem interpretability. The method is characterized by the generation of evaluation conclusions with probabilistic (reliability) information and thus has more advantages than the absolute conclusion form in terms of problem interpretation. Because of the independence of the stochastic simulation solution method, it is applied to the "bottom-up" evaluation model as an example, and a novel autonomous evaluation method is constructed. Finally, the application of the stochastic simulation evaluation model is illustrated by an example and compared with the absolute form evaluation. The evaluation model is an extension of the traditional evaluation model, which can further broaden the practical application of comprehensive evaluation theory.

1. Introduction

The traditional physical education teaching mode is that the physical education teacher repeatedly explains and demonstrates, and the students imitate and practice the movement skills explained by the physical education teacher, so as to accomplish the learning objectives [1]. This traditional PE (physical education) teaching model has many drawbacks and can no longer meet the needs of PE teaching in today's era [2]. The new curriculum reform requires students to be the center and the main body of the classroom, and the traditional physical education teaching mode certainly cannot fulfill the requirements of the new curriculum reform. The traditional PE teaching model is unable to fulfill the requirements of the new curriculum reform [3]. The

informationization of PE teaching can improve the problems in PE teaching, making the PE classroom revolve around students and teachers play a coaching role. As the reform of physical education continues to deepen, it is an inevitable trend for the development of physical education curriculum to replace the traditional physical education teaching mode with information-based physical education teaching [4–9]. On this basis, to find out the shortcomings of the current development of information-based physical education and solve them is an important measure to promote the reform of traditional physical education curriculum [10].

Comprehensive evaluation is the scientific and reasonable use of differential information on the premise that the evaluation information is known, to give a stable and reliable ranking of the program (evaluated object) that is in line with

the objective reality [11]. Comprehensive evaluation is an important part of scientific decision-making and has a wide range of applications in many fields such as engineering design, economic management, and politics and military, attracting the interest of scholars at home and abroad, and has achieved fruitful research results so far [12]. At present, most of the evaluation methods tend to make a one-time absolute judgment on the evaluated object based on the evaluation information, regardless of whether the evaluation information is in the form of precise value or fuzzy number (such as interval, fuzzy number, and linguistic information) [13]. However, for the evaluation problem like "team strength" comparison, it is usually difficult to directly conclude that "team A is absolutely better than team B" from the result of one match, because, either due to equal strength or small probability events, it is very likely that, in the next matches, the team will be better than the team. In the next match, it is likely that "B wins and A loses" [14]. If you think about it, the above questions are also common in reality, such as the comparison of "general ability" and "development potential," which are collectively referred to as "relative evaluation questions" in this paper [15]. In this paper, we refer to these problems as "relative evaluation problems."

In the relative evaluation problem, it is not possible to directly conclude the superiority or inferiority of a solution by only one evaluation run, but it is necessary to statistically analyze the relationship between the superiority and inferiority of solutions on the basis of large-scale comparisons and then to conclude the probability ranking that reflects the relative superiority of solutions [16]. Therefore, first of all, we need to randomize the traditional evaluation method, so that each evaluation run becomes a random sampling of the large-scale run, so that we can get a more stable probability of comparison between the superiority and inferiority of the solutions with sufficient number of simulations. From the above analysis, it is clear that the operation of traditional evaluation method is actually information processing of relative evaluation problem, so the randomization setting of traditional evaluation method should be reflected in the setting of relevant parameters in the evaluation process [17]. As mentioned above, the indicator values of the relative evaluation problem are usually not fixed, which provides the possibility of "random sampling" of the indicator values. In addition, the parameters that can be set randomly are also commonly used for indicator weights, expert authority (group evaluation), information variation treatment (methodological properties measurement), and so on [18].

Based on the randomization setting of the traditional evaluation method, a computer simulation program needs to be developed for large-scale simulation, and the random information extracted each time is solved in the set according to the selected traditional comprehensive evaluation model. The probability information of "better than" or "worse than" between solutions is formed. This paper argues that this absolute form of conclusion hinders the closeness of theory to the essence of the actual problem and is an important reason for the problem of "non-consistency of multiple evaluation conclusions." To address this problem, a stochastic simulation-based comprehensive evaluation solution algorithm based on the idea of "Monte Carlo simulation" is proposed, and the corresponding ranking method is investigated, which is characterized by generating evaluation conclusions with probabilistic (reliability) information and thus has more advantages than the absolute conclusion form in terms of problem interpretability. The method is characterized by the generation of evaluation conclusions with probabilistic (reliability) information and thus has more advantages than the absolute conclusion form in terms of problem interpretation. Because of the independence of the stochastic simulation solution method, it is applied to the "bottom-up" evaluation model as an example, and a novel autonomous evaluation method is constructed. Finally, the application of the stochastic simulation evaluation model is illustrated by an example and compared with the absolute form evaluation. The evaluation model is an extension of the traditional evaluation model, which can further broaden the practical application of comprehensive evaluation theory.

2. Related Work

Relative evaluation problem is a kind of extended definition compared with the traditional evaluation of the object being evaluated in a specific situation (such as examination results and sales performance) and obviously has important theoretical and practical application value for the solution of this kind of problems. However, the "either/or" conclusion form of the traditional evaluation model cannot provide credible conclusions for relative evaluation problems. Based on the idea of "Monte Carlo simulation," the paper gives an idea of how to transform the autonomous evaluation problem into a stochastic evaluation problem and introduces the concept of "likelihood ranking conclusion" for the first time. The "likelihood ranking conclusion" breaks the absolute superiority status of "either-or" among the evaluated objects and is the first exploration of the "relative evaluation problem." Usually, in the relative evaluation problem, the performance (value) of the evaluated object in various aspects (indicators) is not always fixed, but more often fluctuates within a certain range and according to a certain distribution, such as a student's good performance in language, but not always 100 points; the definition of "good" may be above 90 or above 85, etc. [19]. Similarly, this variability in values can be extended to the weighting of indicators and other parameter settings for the evaluation. In addition, because the stochastic simulation solution algorithm has a high degree of independence, it can be added to the evaluation in a "component" way to form a new evaluation method. Based on this, this paper integrates the stochastic simulation solution algorithm with the relative evaluation problem and proposes a new evaluation model, namely, the stochastic simulation evaluation model, and investigates the transformation ideas and solution algorithms between it and the traditional evaluation model [20].

The stochastic simulation-based comprehensive evaluation model is oriented to the relative evaluation problem, as shown in Figure 1, but it is still an information processing method based on the traditional comprehensive evaluation
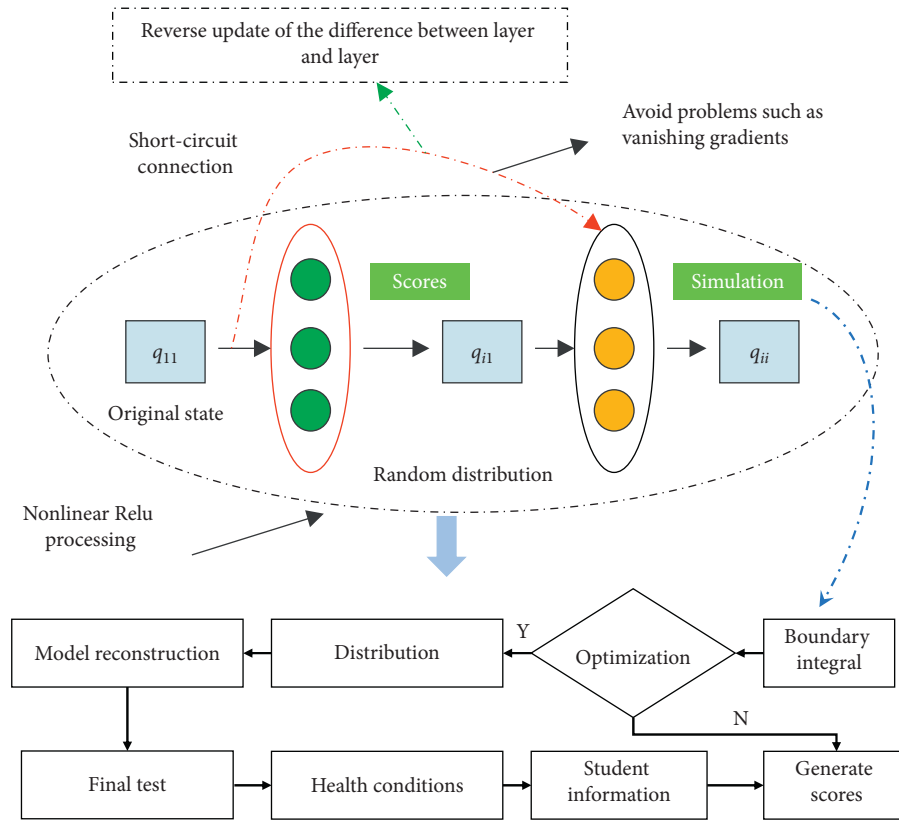
FIGURE 1: Stochastic simulation-based integrated evaluation model.

method, so the stochastic simulation-based comprehensive evaluation model can be regarded as a structured methodological framework, which consists of two parts: one part is the randomized setting of the traditional evaluation method; the other part is the relative evaluation problem based on the stochastic simulation algorithm. The other part is based on stochastic simulation algorithms for solving relative evaluation problems [21].

3. Ideas for Transformation of Traditional Evaluation Models

3.1. Indicator Information Collection. The collection of indicator information, determination of weight coefficients, and selection of information aggregation model are the three main steps in the operation process of traditional comprehensive evaluation (in addition to the clarification of evaluation purpose, determination of evaluation indexes, solution, and analysis of evaluation conclusion), which are also the key to the transformation of traditional comprehensive evaluation mode to stochastic simulation evaluation mode. In this paper, we will introduce the relevant parameters and their setting ideas in the process of transforming the traditional evaluation model to the stochastic simulation evaluation model in accordance with the idea of "expanding from the classical multi-criteria evaluation to its branch areas," and the specific transformation methods will be discussed separately due to the limitation of space. In the relative evaluation problem, the collected evaluation index information is usually not in the form of exact values, but

more in the form of mixed data consisting of exact values, interval numbers, and fuzzy numbers. In the stochastic simulation type evaluation model, the above mixed data should be transformed into the form of random data.

One possible idea is to first determine the range of evaluation indexes, then transform the data into the corresponding range and determine the distribution of the data in the range, and randomly sample the data in the corresponding range according to the distribution. A simple example can be given to illustrate the idea: to evaluate the academic performance of students, the range of values for each subject is between [0, 100], and the physical education score of student A is usually distributed steadily between 75 and 85 and more often between 80 and 85. At this point, we can judge that the range of student A's physical education score is [75, 85], and the density of the distribution between [80, 85] is greater than that between [70, 75]. At this point, it can be assumed that student A's sports performance between [75, 85] obeys normal distribution, and the expected value is between 80 and 85, so the data can be obtained randomly between 75 and 85 according to the normal distribution based on the accurate calculation of the distribution function. It should be pointed out that, in order to eliminate the influence of inconsistency in the evaluation data scale and magnitude on the evaluation results, the original evaluation data should be dimensionless. Generally, there are two kinds of processing ideas: one is to make the whole range of the original evaluation information dimensionless before random sampling; the other is to make the randomly obtained data after random sampling dimensionless in the same way.

The latter approach is recommended to avoid the damage to the internal structure of the original data that may result from the overall dimensionless processing of the range of values of the original evaluation information. The above transformation ideas can be further extended to the following evaluation problems: ① uncertainty evaluation problems, such as evaluation information in the form of interval, triangular fuzzy number, and linguistic information; ② evaluation method nature test problems, such as measuring the structural stability of an evaluation method, which can usually observe the degree of interference in the process of a sudden change of an index from normal to abnormal values; ③ the comparative analysis of multiple evaluation methods, such as comparing multiple evaluation methods. (3) Comparative analysis of multiple evaluation methods, such as comparing the sensitivity of several information aggregation patterns, generally cannot be concluded from only one set of data, but need to draw a more stable comparative conclusion based on a large number of randomly obtained data.

3.2. Weighting Factor Determination. Similarly, when the collected index weight information is incomplete, such as $w_1 > w_2, w_3 \in [0.3, 0.5]$, it is necessary to further negotiate to determine the range of the corresponding weight coefficients and their distribution states and to randomly obtain the data with the corresponding distribution states in the range of values. The idea of random transformation of weight coefficients can be further extended to the following:

(1) Defining expert authority in group evaluation.

(2) Determination of the importance level of various evaluation methods in portfolio evaluation.

(3) Determination of time weighting coefficients in dynamic evaluation. Another way of randomization of the weight coefficients is that when the weight coefficients are given by certain expressions, the relevant parameters in the expressions can be set according to certain rules to achieve the measurement of the effect of satisfying a specific evaluation objective, such as the problem of setting the weight coefficients to highlight their advantages in autonomous evaluation.

After clarifying the evaluation purpose and collecting the evaluation information, it is usually difficult to choose the evaluation method (mainly the information aggregation model), such as whether to choose the WGA or WAA algorithm for information aggregation. One feasible idea is to test the evaluation methods on the premise of clarifying the evaluation purpose and the degree of satisfaction of the evaluation purpose. The test should be based on the comprehensive simulation of the number of evaluation indexes, dimensionless methods, and relevant parameters in the expressions of weight coefficients, etc., to obtain the stable measure of the satisfaction degree of the evaluation purpose of the method.

3.3. Stochastic Dynamic Simulation Algorithm. Relative evaluation problems cannot directly determine the superiority or inferiority of a solution in a specific assessment, but it is necessary to analyze statistically the relationship between superiority and inferiority of the solution on the basis of a large comparison. Then close probability rankings that reflect the relative advantages of the solution. The concept of "superiority matrix" is to count the number of "better than" and "worse than" comparisons between two solutions during the stochastic simulation and divide the number of superiority and inferiority by the total number of simulations at the end of the simulation to obtain the probability of "better than" and "worse than" comparisons between two solutions. The probability of "better than" and "worse than" is obtained by dividing the number of better and worse by the total number of simulations at the end of the simulation, and the probability ranking with probability characteristics between the solutions is derived. In general, the general form of the superiority matrix for the comparison between n solutions (denoted by o_1, o_2, ..., o_n), provided that the simulation is sufficient, is

$$Q = \begin{bmatrix} q_{11} & q_{12} & \cdots & q_{1n} \\ q_{21} & q_{22} & \cdots & q_{2n} \\ \cdots & \cdots & \cdots & \cdots \\ q_{n1} & q_{n2} & \cdots & q_{nn} \end{bmatrix}. \tag{1}$$

Theoretically, if all elements of the matrix S are not zero, then $n!$ sorting chains can be derived from the matrix S, and each sorting chain can occur with different probabilities. The probability of each chain is different, and the stability of each chain is also different. Here, we refer to the probability of occurrence of the chains as the "likelihood factor" and the overall stability of the chains as the "stability factor." If $s_{ij} = 0$ holds for a certain chain, it is obvious that the chain does not hold; i.e., the chain cannot occur. Therefore, the minimum s_{ij} in a chain can be used to represent the probability coefficient of the chain. The probability and stability coefficients of the chain are denoted by p and t, respectively, and we have the following.

Definition 1. For a sorted chain $o_1 \xrightarrow{s1'2'} o_2 \xrightarrow{s2'3'} \ldots o_n$, call

$$p = \min\{q_{ij}\}, \quad i < j; i = 1, 2, \ldots, (n-1), \tag{2}$$

the likelihood coefficient of the sorted chain, with $p \in (0, 1]$.

Definition 2. For a sorted chain $o_1 \xrightarrow{s1'2'} o_2 \xrightarrow{s2'3'} \ldots o_n$, call

$$t = \prod_{i=1}^{n-1} \prod_{j=i+1}^{n} q_{ij}, \tag{3}$$

the stability coefficient of the sorted chain, with $t \in (0, 1]$.

4. Establishment of Comprehensive Evaluation Algorithm

4.1. Inverted Sorting Method. Based on the rule of "further guaranteeing the stability of the sorting chain by increasing the probability of its occurrence," we propose an algorithm for solving the conclusion of the probability sort, which is called "reverse sorting," which can be referred to as in Figure 2.

Step 1. The smallest element (set to q_{ij}) of the superiority matrix Q is selected, and to avoid the possibility coefficient of the sorting chain q_{ij}, o_{joi} can be assumed, which reverses the possibility of o_{ioj} represented by q_{ij} to increase the possibility coefficient of the sorting chain; when the matrix S is more than one smallest element in the matrix S, the corresponding scheme can be similarly inversely sorted according to the previous assumption.

Step 2. The next smallest element of the superiority matrix Q (set to q_{km}) is selected, and similarly, to avoid the probability factor of the sorting chain to be q_{km}, it can be assumed that $om > ok$.

Step 3. The inverse sorting process is similar to the inverse sorting process in Step 1 and Step 2, until a circular sorting chain appears or all solutions are sorted. When there is a circular sorting chain, the sorting among the solutions corresponding to the largest element selected in the first 3 steps is reversed again, and the solution of the reversed sorting process is selected based on the highest probability coefficient of the reversed sorting chain, and if there are multiple acyclic sorting chains with the same probability coefficient after reversal, the sorting chain with the highest stability coefficient prevails.

Step 4. If the obtained ranking chain is the overall ranking of all solutions, the whole ranking process is finished, and the probability and stability coefficients of the ranking chain can be obtained according to Definition 1 and Definition 2; otherwise, on the basis of Step 3, the corresponding solutions are sorted in reverse order from the smallest to the largest elements of the superiority matrix, until the overall ranking of all solutions is obtained. The overall ranking of all solutions is obtained.

The inverse sorting method starts with the smallest superiority element and finds the inverse order between the two solutions, so that, regardless of whether there is a circular chain between the remaining solutions, the possibility of the corresponding sorting chain between the remaining solutions is always greater than c. Therefore, the probability factor of the probability of termination of the probability gradient is equal to the maximum value of the elements of the superiority matrix between solutions that are not reversed when the first circular chain is displayed. The conclusion was proven.

4.2. Inverted Sorting Method to Solve. If there is a circular chain, the probability coefficient of the solution is equal to the maximum value of the elements of the superiority matrix
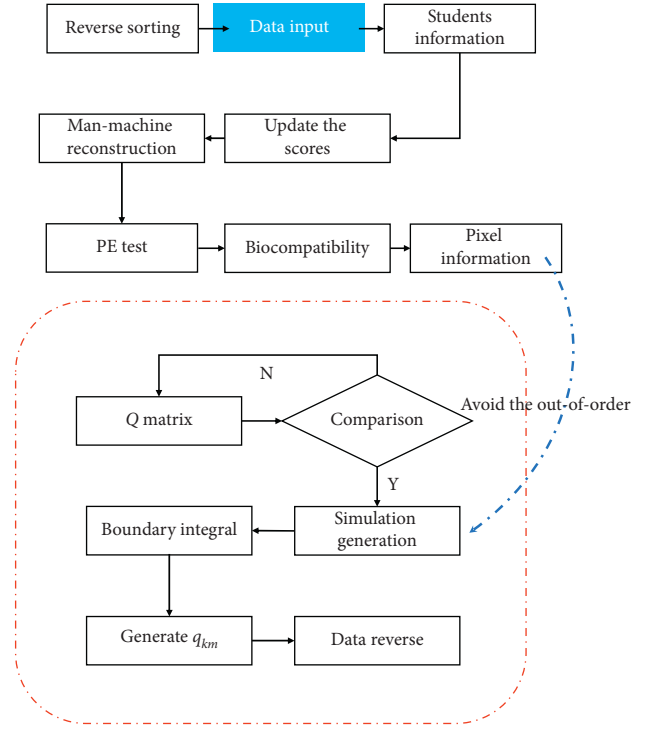

Figure 2: Inverted sorting method.

between the solutions without reversal when the first circular chain occurs, as shown in Figure 3.

Let the first cyclic chain consist of m schemes, where $q_{2'1'} = a$, $q_{m'(m-1)'} = b$, $q_{m'1'} = c$, and $a < b < c$.

(1) If $a = b = c = 0.5$, then the probability of occurrence of any sorting chain is the same and is 0.5. In this case, the probability coefficient of the conclusion of the possibility sort is equal to the maximum value of 0.5 of the elements of the superiority matrix corresponding to the uninverted sort between the solutions when the first cyclic chain occurs.

(2) If $a, b, c \neq 0.5$, we have $a, b, c < 0.5$ because the inverse sorting method starts from the smallest superiority element to find the inverse order between two solutions.

If we break the chain from ①, we have $o1' > o2' > ...om'$, because $a < b < c$, so $1 - a > 1 - b > 1$—so the probability factor of the sorted chain is c.

If we break the chain from ②, we have $o_{2'}...o_{m'o1'}$, and since $s_{2'1'} = a$ minimum, the probability factor of the sorted chain is a.

If the circular chain is broken from ③, we have $o_{m'o1'}...o_{(m-1)'}$, since $s_{m'(m-1)'} = b$ is the smallest, so the probability factor of the sorted chain is b.

From the viewpoint of improving the possibility of the sorting chain, we should choose to break the circular chain from ①, and the possibility coefficient of the sorting chain of m solutions is c. Since the inverse sorting method starts from the smallest superiority element to find the inverse order between two solutions, the possibility of the corresponding sorting chain between the remaining solutions is always
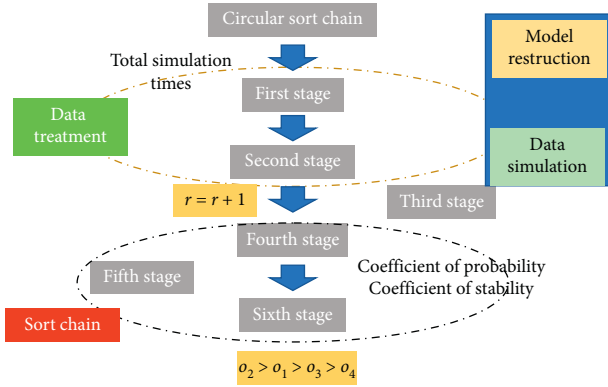
FIGURE 3: Circular sorting chain.

greater than c, regardless of whether there is a circular chain between the remaining solutions. Therefore, the probability coefficient of the conclusion of the possibility ranking is equal to the maximum value of the elements of the superiority matrix between the solutions that are not reversed when the first circular chain appears. The conclusion is proved.

When the number of solutions is large, it is tedious to determine the ranking of solutions one by one using the above procedure, which requires high endurance of the evaluator. Based on this, we adopt the idea of "random simulation to find the most probable and stable ranking chain among the $n!$ ranking chains derived from the superiority matrix" to solve the probability ranking conclusion as follows.

Step 1. Set the total number of simulations sum (initial value is 0; in general, the higher the number of scenarios n, the higher the value of sum should be), the count variable r (initial value is 0), and the statistical variables $p_0 = 0$, $t_0 = 0$, $X_0 = [0]_{1 \times n}$, $X^* = [0]_{1 \times n}$.

Step 2. The random series generation function randperm(n) is used to generate a random series of length, denoted as X.

Step 3. If $X \neq X_0$, let $r = r + 1$ and use the elements in X as subscripts of the solutions and determine the "better than" order among the solutions based on the positions of the elements in X.

Step 4. Let $X_0 = X$. Calculate the probability and stability coefficients of the sorting chain in Step 3, denoted as p and t, respectively.

Step 5. If $p > p_0$ or $p = p_0$ and $t > t_0$, then $p_0 = p$, $t_0 = t$, and $X^* = X$. Go to Step 2; otherwise, go to Step 6.

Step 6. If $r = n!$, then save the values of p_0, t_0, X^* and end the program; otherwise go to Step 2.

The "better-than" order among the solutions with the elements in X^* as subscripts and the positions of the elements in X^* is the required probability ranking conclusion. Based on the above simulation steps, the program is written to solve the probability ranking conclusion for the superiority matrix in example 1, and the obtained ranking chain is $o2 > o1 > o3 > o4$, and the probability coefficient of this

ranking chain is 0.4 and the stability coefficient is 0.0645, which is consistent with the conclusion of the "inverse ranking method." The stability coefficient is 0.0645, which is consistent with the conclusion of the "inverse sorting method." This works by generating several classifiers from which everyone learns and predicts independently. These predictions are eventually combined into a single prediction, so they are better than a single classification to make predictions. As a new and flexible integrated learning algorithm, it cuts sharply in many specific issues and is widely used in sectors ranging from finance, finance, and health care, both in the assessment of financial risk and in the forecasting of sports ratings for listed companies.

4.3. Stochastic Dynamic Forest Algorithm. Random forest is a subclass of integrated learning, which solves a single prediction problem by building a combination of several models. Its basic unit is a decision tree, an algorithm that integrates multiple decision trees through the idea of integrated learning, relying on the voting choice of the decision trees to determine the final classification result. It works by generating multiple classifiers, each learning and making predictions independently. These predictions are finally combined into a single prediction and therefore outperform any single classification to make a prediction. As an emerging and highly flexible integrated learning algorithm, it has shown powerful performance in many specific problems and has been widely used in various industries, from finance to health care, both for assessing the financial risk of listed companies and for predicting sports evaluation probabilities. The implementation process of the random forest algorithm is divided into the following 3 main steps.

(1) A random forest with many decision trees is built in a random way, where individual decision trees are generated randomly and there is no specific association between two different decision trees. Assume that the training set size is N. For each tree, the bootstrap sample method is used to randomly and releasingly draw N training samples from the total training set as the training set of the tree, and the training set of each tree is different and contains duplicate training samples.

(2) During the growth of each tree, the features are randomly selected to split the internal nodes of the decision tree. Commonly used decision tree splitting algorithms include C4.5 algorithm, ID3 algorithm, and CART algorithm. Suppose the feature dimension of each sample is M. According to the principle of exponential minimum, a constant $m << M$ is specified, and a subset of m features is randomly selected from the M features, and the optimal one is chosen from these m features each time the tree is split. These selected features are called random feature variables.

(3) The samples to be processed are input into the random forest, and each decision tree in the forest makes a classification judgment separately to decide

which category the input samples should belong to, then aggregates the judgment results of all N decision trees, votes on each record according to the N classification results, and finally takes the classification result with the largest number of records as the final output of the algorithm.

According to the idea and implementation process of random forest algorithm, the grade early warning model designed in this paper takes a large number of previous students' grade data in the academic affairs system as the total training set, adopts bootstrap sample method, extracts N training samples as the training set, forms N unrelated decision trees, and then selects relevant course scores as random feature variables; each decision tree makes a prediction of students' grades according to its own training set and finally integrates the prediction results of each decision tree to form a judgment on the final direction of students' future grades. Each decision tree makes a prediction of students' performance based on its own training set and finally integrates the prediction results of each decision tree to form a judgment on the final direction of students' future performance. The model is shown in Figure 4.

5. Application of Evaluation Scores Based on Stochastic Dynamic Models

Suppose the student to be predicted is Zhang San, a 2017 student of automation in a university, and the course to be predicted is "Physical Education" in the next academic year. According to the predicted course grades, there are three warning risk levels: predicted grades below 60 are high risk, predicted grades between 60 and 75 are medium risk, and predicted grades above 75 are low risk. In this paper, 4,540 grades of 65 students in the university are used as the total training set, and the random forest early warning model proposed in this paper is used to model the students' grades and finally generate the early warning risk level for Zhang San's major course "System Integration Technology."

A random total structure with four decision trees is formed by using Bootstrap sample methods to extract a sample of four classes progressively as a training set and then to determine the number of random features of each decision tree as 1, depending on the actual situation. Then select a note for the current note as a random feature variable for each decision structure. Decision Tree 1 uses "basketball" as a random feature variable, Decision Tree 2 uses "football" as a random feature variable, Decision Tree 3 uses "badminton" as a random feature variable, and Decision Tree 4 uses "Running" as a random. Decision Tree 4 uses "Running" as a random feature variable. After the calculation, the risk distribution for each decision tree of the target course "System Integration Technology" is shown in accordance with the initial training set above. The training sessions and training results for the four decision trees above represent a specific random selection, which is used as the core of the performance warning model and as a result as sample input for four main courses for pupil Zhang San for the current
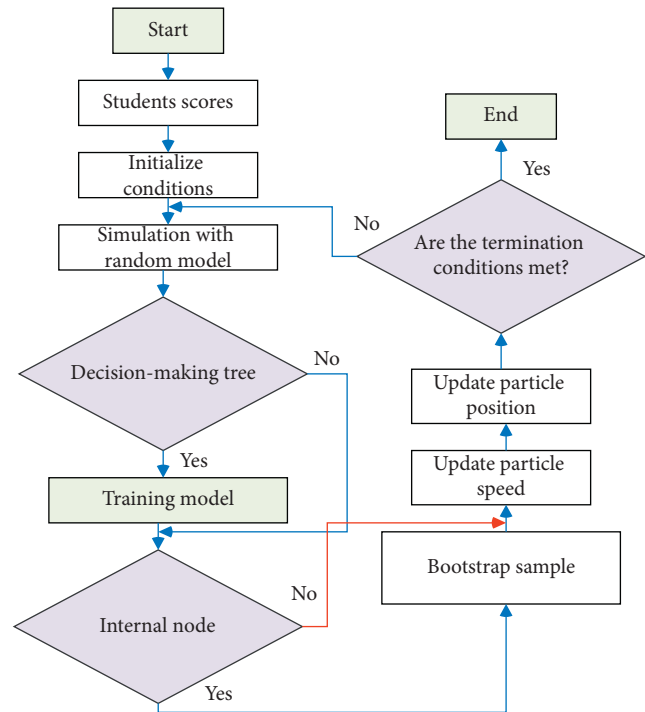

Figure 4: Principles of random forest algorithm.

school year. As shown in Figure 5, the likelihood of a student's performance in the eligible course "Physical Education" for the next school year is low, with a high and low risk of 4.9%, respectively. 24.0%. The probability of medium risk is greater with 66.2%.

In this paper, we propose a college student grade warning model based on random forest algorithm in the context of big data to address the lag and limitation of existing college student grade warning, as shown in Figure 6. By deeply analyzing the existing grades of students of the same majors in colleges and universities, mining the potential patterns of the grade data, forming different training sets from a large number of grade data, then forming several decision trees to predict students' grades separately, and finally combining the prediction results of all decision trees to arrive at the risk level of students' grades. The early warning model has been proven to be effective in improving the existing performance warning mechanism, enabling early warning to be generated, providing technical support for early intervention in students' poor academic performance and improving the quality and effectiveness of students' learning. The physical education class itself is based on physical exercises, and students have to finish a class in constant movement, but teachers often repeatedly explain the technical movements in order to make students understand them better, which defeats the original purpose of physical education class. In the process of physical education, the teaching content of the demonstration of the use of information technology teaching means, first, through information technology means to explain the teaching content more detailed, so that students are more intuitive, accurate mastery of the important points of the action skills. Second, through repeated action demonstration to help students in
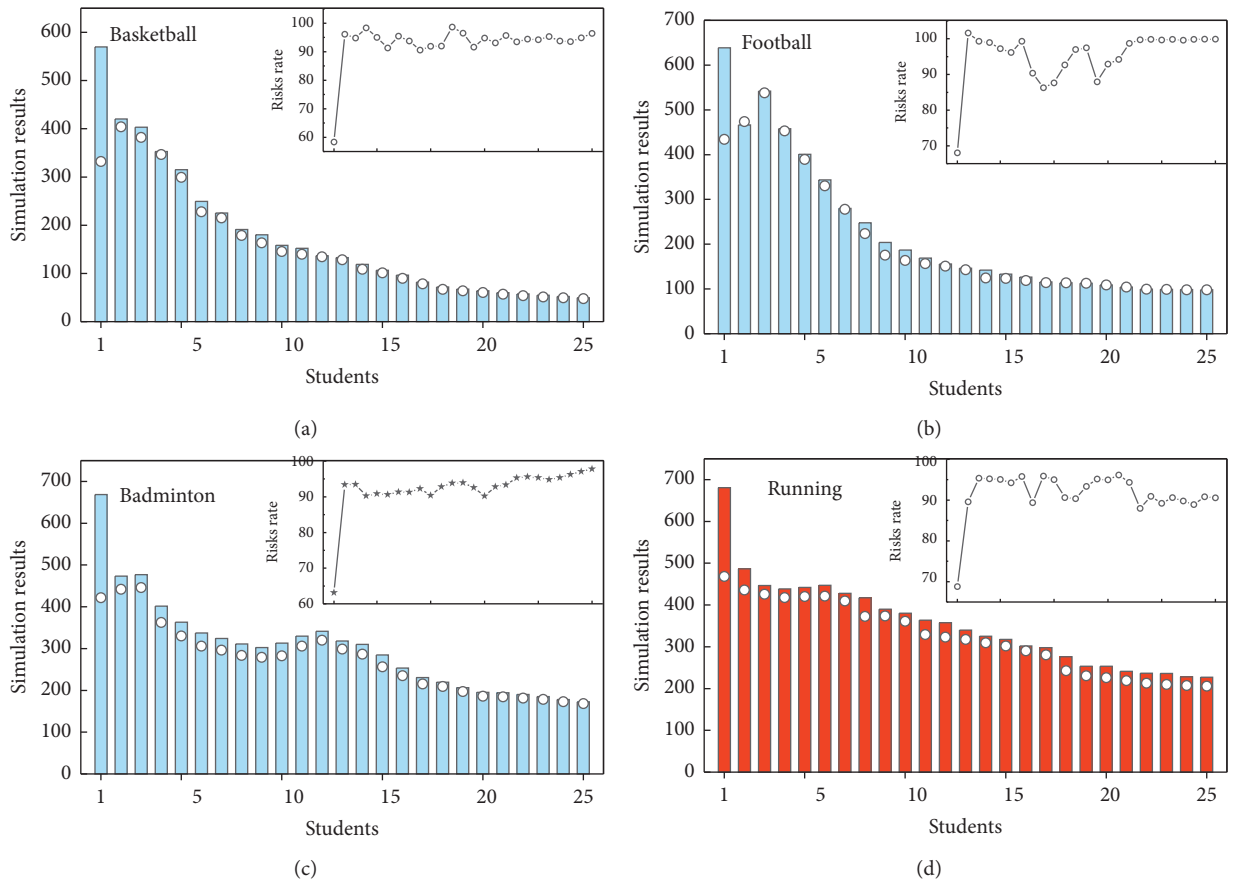
(a)

(b)

(c)

(d)

FIGURE 5: Decision tree predictions for basketball, soccer, badminton, and running performance.
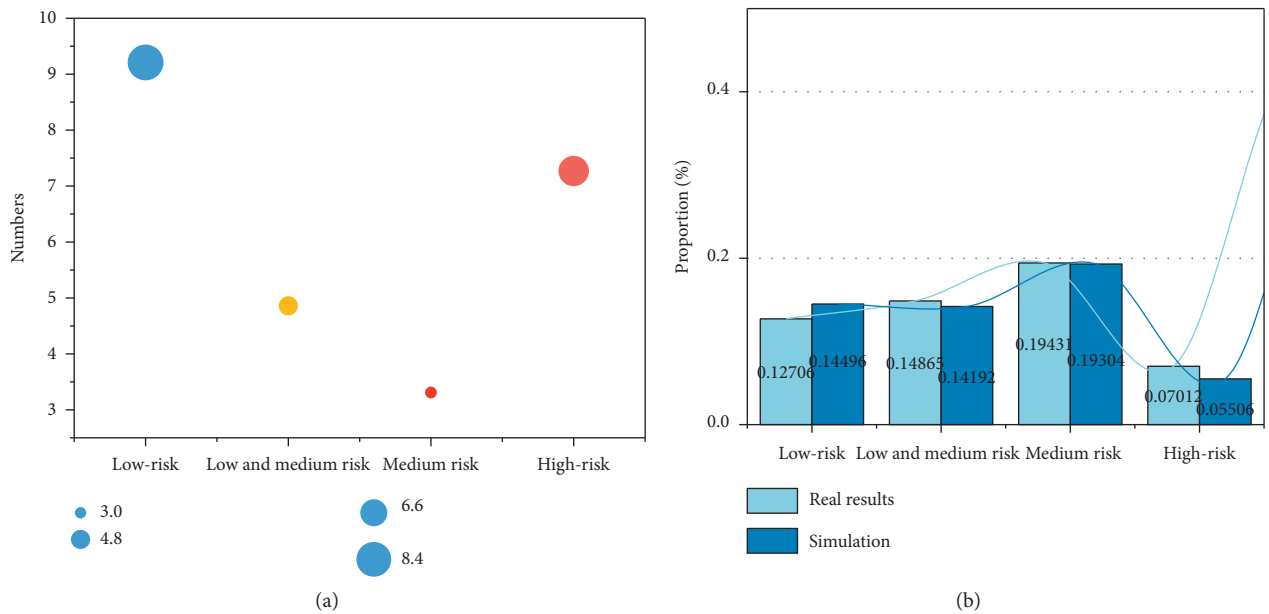

(a)

(b)

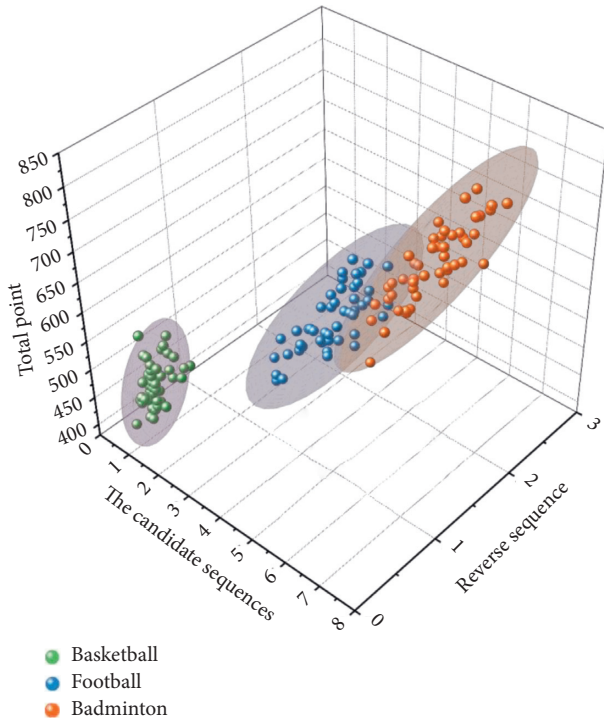FIGURE 6: Student performance alert in higher education.

Figure 7: Stochastic simulation method for solving.

the mind to more accurately establish the concept of action, save the time of physical education teachers in the explanation and demonstration, improve teaching efficiency, but also to a certain extent to ensure the teaching of the practice density, to achieve precision lectures more practice.

For the sake of simplicity, the values of the 10 students in the range of subject scores are assumed to be uniformly distributed. The random number generator is used to generate random data in the range of the subject scores (note: the random data are taken as integers to better fit the reality), and then the total scores of the 10 students are calculated, and the number of times they are superior or inferior to each other is counted and the probability of superiority or inferiority is calculated to obtain the superiority matrix of the 10 students as follows:

$$Q = \begin{bmatrix} 0.125804 & 0.127064 & 0.144957 & 0.19672 & 0.20123 & 0.3612 \\ 0.151384 & 0.148653 & 0.141916 & 0.3908 & 0.3944 & 0.2432 \\ 0.178983 & 0.194305 & 0.193044 & 0.161088 & 0.118208 & 0.24353 \\ 0.077786 & 0.070116 & 0.055056 & 0.4439 & 0.4859 & 0.1541 \\ 0.448766 & 0.441147 & 0.443487 & 0.42608 & 0.44439 & 0.0757 \\ 0.017277 & 0.018715 & 0.021541 & 0.47727 & 0.50217 & 0.05673 \end{bmatrix}.$$

(4)

The probability chains obtained by the "inverse ranking method" and the stochastic simulation method are $o5 > o8 > o7 > o6 > o4 > o9 > o1 > o2 > o3 > o10$, and the probability coefficient of this ranking chain is 0.5406, and the stability coefficient is 0.0529, as shown in Figure 7.

If the results of each candidate are aggregated directly according to the traditional evaluation model (choosing the midpoint of the interval as the evaluation data), the total

results of each candidate (expressed as y_i) are $y_1 = 540$, $y_2 = 537.5$, $y_3 = 526$, $y_4 = 574.5$, $y_5 = 599.5$, $y_6 = 575.5$, $y_7 = 593$, $y_8 = 596$, $y_9 = 540.5$, $y_{10} = 521.5$. 5, $y_7 = 593$, $y_8 = 596$, $y_9 = 540.5$, and $y_{10} = 521.5$, resulting in the ranking of candidates as $o5 > o8 > o7 > o6 > o4 > o9 > o1 > o2 > o3 > o10$, in which the position of each candidate in this ranking is the same as the position of each candidate in the possibility ranking, but the absolute superiority of each candidate in this ranking is compared. Looking at the values of y_9 and y_1, we can see that the total score of $o9$ is only 0.5 points higher than that of $o1$, so there is no guarantee that o_9 will outperform o_1 in the final exam. This ranking conclusion is more realistic and acceptable.

6. Conclusion

The random simulation evaluation model is an extension of the traditional evaluation model, providing a structural framework for various forms of information and evaluator preferences, so that the evaluation process is no longer limited by a single or limited form of data and information structure, which can further enhance the practical application of comprehensive evaluation methods. The conclusions of probability ranking with probability characteristics are more explanatory and acceptable for relative evaluation problems. Specifically, the stochastic simulation-based evaluation method has the following three main features: (1) the evaluation problem is fully solved by simulation, avoiding the situation that the conclusion is not fully solved by one evaluation; (2) in the simulation process, the probability of superiority and inferiority among the solutions is counted in the way of the superiority matrix, which lays the foundation for the conclusion of the likelihood ranking. In the simulation process, the superiority matrix is used to calculate the probability of superiority among the solutions, so as to lay the foundation for the solution of the probability ranking conclusion, which is an extension of the absolute ranking conclusion and avoids the "either-or" conclusion among the solutions. Through the setting of relevant parameters, the traditional evaluation methods are integrated into the solution process of the stochastic simulation, especially to provide a convenient way for the comparison of multiple similar evaluation methods. (3) The traditional evaluation methods are integrated into the solution process of stochastic simulation by setting the relevant parameters, especially for comparing multiple similar evaluation methods.

Data Availability

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

Conflicts of Interest

The author declares no conflicts of financial interest or personal relationships that could have appeared to influence the work reported in this paper.

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