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Retraction

Retracted: A Study on the Usefulness of Stochastic Simulation Algorithms for Teaching and Learning in College Physical Education Classrooms

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This article has been retracted by Hindawi following an investigation undertaken by the publisher [1]. This investigation has uncovered evidence of one or more of the following indicators of systematic manipulation of the publication process:

(1) Discrepancies in scope
(2) Discrepancies in the description of the research reported
(3) Discrepancies between the availability of data and the research described
(4) Inappropriate citations
(5) Incoherent, meaningless and/or irrelevant content included in the article
(6) Peer-review manipulation

The presence of these indicators undermines our confidence in the integrity of the article's content and we cannot, therefore, vouch for its reliability. Please note that this notice is intended solely to alert readers that the content of this article is unreliable. We have not investigated whether authors were aware of or involved in the systematic manipulation of the publication process.

Wiley and Hindawi regrets that the usual quality checks did not identify these issues before publication and have since put additional measures in place to safeguard research integrity.

We wish to credit our own Research Integrity and Research Publishing teams and anonymous and named external researchers and research integrity experts for contributing to this investigation.

The corresponding author, as the representative of all authors, has been given the opportunity to register their agreement or disagreement to this retraction. We have kept a record of any response received.

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[1] J. Xu, "A Study on the Usefulness of Stochastic Simulation Algorithms for Teaching and Learning in College Physical Education Classrooms," *Mathematical Problems in Engineering*, vol. 2022, Article ID 2779909, 6 pages, 2022.

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Research Article

A Study on the Usefulness of Stochastic Simulation Algorithms for Teaching and Learning in College Physical Education Classrooms

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In order to address the problem of the absolute nature of the evaluation of superiority and inferiority in the evaluation of physical education classroom in universities and the problem of inconsistency in the conclusion of multiple evaluations, we develop an "autonomous advantage evaluation method to highlight one's own advantages," which uses a probabilistic stochastic simulation algorithm to evaluate the advantages of the evaluated objects by calculating the degree of superiority among them. The method is based on an innovative "base to top" approach, with a high degree of independence. The method was validated by means of an algorithm, and the conclusions were obtained with probabilistic information.

1. Introduction

University students are the future pillars of our country, and it is only when they have a healthy body that they can be most creative and create more value. Therefore, it is very important for universities to provide physical education to students [1]. The health of students is reflected in all aspects of their lives, and physical education is an integral part of it, as learning more about physical education and acquiring skills through practical application can enhance students' physical fitness [2]. The Ministry of Education is paying more and more attention to the health of students, requiring universities to make reasonable physical education programs to improve the physical fitness of students, and according to the regulations, each school is constantly correcting and improving its teaching methods, and gradually tends to diversify and enrich the teaching content [3–5]. Therefore, it is important to evaluate the quality of physical education in order to judge the quality of teaching and learning [6–8]. Data mining is a popular data analysis technology that has received widespread attention. This technology can use known data resources to discover more potential information and the connection between things, firmly grasp this technology and apply it to the evaluation of the quality of physical education in college students, you can find out the factors affecting the quality of physical education and effectively enhance the physical fitness of students [9–12].

In China, physical education classroom teaching has been developed for many years, and even though the mechanism of the method varies and the way of solving the problem is different, the conclusion form is mostly determined and consistent, which is expressed as "the absoluteness of superiority and inferiority discrimination" and "the strictness of difference transmission " [13–15]. The use of different evaluation methods for the same evaluation problem usually results in different evaluation conclusions, resulting in the problem of "nonconsistent multievaluation conclusions" [16]. It is now generally accepted that 'portfolio evaluation' is an effective solution to this problem, but in reality, this is a compromise approach that does not address the essence of the problem at its root [17].

In this paper, we develop an "autonomous advantage evaluation method to highlight one's own advantages," which uses a probabilistic stochastic simulation algorithm to evaluate the advantages of the evaluated objects by calculating the degree of superiority among them [18]. This method produces probabilistic (reliable) evaluation conclusions, which are more interpretable to the actual problem, and proposes an innovative "base to top" comprehensive evaluation method with a high degree of independence, which is added to the evaluation in the form of "components." The method is based on an innovative "base to top" approach, with a high degree of independence. The validity of the method is verified by means of an example [19].

2. Basic Description of Assessment Issues in Physical Education

There is a multi index evaluation system $x_{ij} = x_j(x_i)$, $(i = 1, 2, \ldots, n; j = 1, 2, \ldots, m)$ composed of $u_1, u_2, \ldots, u_n$, m evaluated objects and $x_1, x_2, \ldots, x_m$ indexes, which is about index x_j for the evaluated object u_i; observed value of the evaluation data matrix (decision matrix) can be expressed as

$$A = \left[x_{ij}\right]_{n\times m} = \begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1m} \\ x_{21} & x_{22} & \cdots & x_{2m} \\ \cdots & \cdots & \cdots & \cdots \\ x_{n1} & x_{n2} & \cdots & x_{nm} \end{bmatrix}, \tag{1}$$

where $m, n \geq 3$, and the data in A is the normalized data after preprocessing the physical education evaluation process we describe as a general transformation:

$$y_i = f\left(x_{i1}, x_{i2}, \ldots, x_{in}\right), \quad i \in N, \tag{2}$$

where f is the positive transformation function; y_i is the comprehensive evaluation value of the object u_i being evaluated, and $u_1, u_2, \ldots, u_n$ is ranked according to the $u_1, u_2, \ldots, u_n$ value from the largest to the smallest, to complete the $u_1, u_2, \ldots, u_n$ comparison of the advantages and disadvantages.

3. Description of the Autonomous Strengths Assessment

Hypothesis 1. is that each of the evaluated subjects has the dual objective of "widening the gap between competitors" and "developing their own strengths," and in doing so, highlights their own strengths in an integrated manner.

A quantitative description of the idea of autonomous strengths evaluation in hypothesis 1:

Definition. α_{ij}, β_{ij} is the amount of column and row dominance of the evaluated object $u_i (i \in N)$ on indicator $x_i (i \in N)$, respectively, and satisfies

$$\begin{cases} \alpha_{ij} = \dfrac{1}{n-1} \displaystyle\sum_{k\neq i} \left(x_{ij} - x_{kj}\right), & i \in N, \quad j \in M, k \in N, \\ \beta_{ij} = \dfrac{1}{m-1} \displaystyle\sum_{p\neq j} \left(x_{ij} - x_{ip}\right), & i \in N, \quad j \in M, p \in M. \end{cases} \tag{3}$$

If we let $\lambda_{ij} = \mu\alpha_{ij} + \eta\beta_{ij}$, $\quad i \in N$, $j \in M$, then we say that λ_{ij} with is the amount of autonomous advantage of the evaluated object $u_i (i \in N)$ with respect to indicator $x_j (i \in N)$, where μ is the competitive target coefficient and n is the developmental target coefficient $\mu, \eta \in [0, 1], \mu + \eta = 1$.

Column dominance $\alpha_{ij} (i \in N, j \in M)$ reflects the difference in strength between the jth indicator of the evaluated object μ_i and the n-1 other evaluated objects as a whole, while row dominance β_{ij} reflects the difference in strength between the jth indicator of the evaluated object μ_i and the m-1 other indicators as a whole.

4. Stochastic Simulation Algorithm

4.1. Nonlinear Programming Problems Where the Objective Function Is Linear. This paper gives a simulated annealing and evolutionary planning algorithm for nonlinear planning problems with linear objective functions, which transforms problems with constraints into unconstrained ones. Numerical results confirm the high computational accuracy of the method and show good convergence, considering the following optimization problem (where c is a vector):

$$\begin{aligned} &\min c^T x \\ &\text{s. t.} \begin{array}{l} g_i(x) \leq 0 \quad i = 1, \ldots, r \\ Ax \geq b \end{array} \end{aligned} \tag{4}$$

In order to find a feasible solution that satisfies the constraint, we first solve the subproblem:

$$\begin{aligned} &\min, f = \max\{0, g_i(x) \quad i = 1, \ldots, r\}, \\ &\text{s.t.} \begin{array}{l} c^T x \leq c^T x_k^* - \varepsilon, \\ Ax \leq b, \end{array} \end{aligned} \tag{5}$$

where x_k^* is the optimal solution at k steps and ε is a small positive number. Let $B = \begin{pmatrix} C^T \\ A \end{pmatrix}$, $d = \begin{pmatrix} c^T x_k^* - \varepsilon \\ b \end{pmatrix}$, the constraint can be reduced to $\mathrm{B}x \leq d$.

$\mathrm{B}x \leq d$ can be written as

$$\begin{cases} b_{11}x(1) + b_{12}x(2) + \cdots + b_{1n}x(n) \leq d_1, \\ b_{21}x(1) + b_{22}x(2) + \cdots + b_{2n}x(n) \leq d_2, \\ \qquad\qquad \cdots \\ b_{m+1,1}x(1) + b_{m+1,2}x(2) + \cdots + b_{m+1,n}x(n) \leq d_{m+1}. \end{cases} \tag{6}$$

4.2. Simulated Annealing Algorithms for Nonlinear Programming Global Optimization Problems. Based on the upper and lower bounds of component $x(L_i)$, we propose a class of simulated annealing algorithm for solving subproblem (3). The specific steps of the algorithm are as follows: Algorithm 1:

Step 0: initialization: the maximum and minimum temperatures are $T_{\max}$, $T_{\min}$, the number of iterations $L_{\max}$ and the parameters are given respectively $\varepsilon > 0$.
Step 1: use the random process to obtain the initial value of the feasible solution $x_0 = (x_0(1), \ldots, x_0(n))$, set $T = T_{\max}$, $t = 0, I = 0$. If f $(x_0) \leq 0$, then I = 1, $y^* = x_0$. Otherwise, turn to step 2.
Step 2: While $(T > T_{\min})$ do
(a) while $t \leq L_{\max}$ do
(1) randomly select $l_t \in \{1, 2, ..., n\}$, and give a uniformly distributed random number $\lambda \in [-1, 1]$. For $j = 1, ..., n$, if $\lambda > 0$.

$$z(j) = \begin{cases} x_t(j) + \alpha \times (b_{l_t} - x_t(j)) \times \lambda, & \text{if } j = l_t \text{ and } b_{l_t} \neq \infty, \\ x_t(j) + \alpha \times \lambda, & \text{if } j = l_t, b_{l_t} = \infty, \\ x_t(j), & \text{if } j \neq l_t. \end{cases}$$

$$z(j) = \begin{cases} x_t(j) + \alpha \times (x_t(j) - a_{l_t}) \times \lambda, & \text{if } j = l_t \text{ and } a_{l_t} \neq \infty, \\ x_t(j) + \alpha \times \lambda, & \text{if } j = l_t, a_{l_t} = \infty, \\ x_t(j), & \text{if } j \neq l_t, \end{cases}$$

where a_{l_t} and b_{l_t} are lower and upper bounds, $x_t(l_t)$ comes from Algorithm 1, α The initial value of is 1, if 444, then $\alpha = 1$.
(2) let $z = (Z(1), ..., Z(n))$, if f $(z) \leq 0$, then $I = 1$, $y * = Z$. Algorithm 1 stops. Otherwise, turn (3).
(3) Take $\eta \in [0,1]$, if $\eta \leq \min\{1, \exp[f(x_t) - f(z)]/T\}$, set $x_{t+1} = z$, otherwise $x_{t+1} = x_t$, $t = t + 1$.
(b) $L_{\max} = L_{\max} + d$, $t = 0$.
(c) by $T = \delta \times T$ lower the temperature T. Where parameter D, β And δ is a known constant entered in advance.

Algorithm 1

Step 1: Given μ initial values, let $k = 1$ and I = 0. Let the individuals be real-valued vector pairs (x_i, η_i), $\forall i \in \{1, \ldots, \mu\}$ [20–22].
Step 2: Calculate the individual adaptation value. If $\exists i \in \{i, \ldots, \mu\}$, $f(x_i) \leq 0$, then $I = 1, y^* = x_i$ otherwise turn Step 3.
Step 3: For each parent (x_i, η_i), $\forall i = 1, \ldots, \mu$, generate a child (x_i', η_i') according to the following steps: Randomly select l_i from the set { 1, 2, ..., n} to generate a uniformly distributed random parameter λ in the interval [- 1, 1]. For $j = 1, ..., n$, if $\lambda > 0$

$$x_i'(j) = \begin{cases} x_i(j) + \eta_i(b_j - x_i(j))\lambda, & \text{if } j = l_i \text{ and } b_{l_i} \neq \infty, \\ x_i(j) + \eta_i\lambda, & \text{if } f = l_i, b_{l_i} = \infty, \\ x_i(j), & \text{if } j \neq l_i. \end{cases}$$

$$x_i'(j) = \begin{cases} x_i(j) + \eta_i(x_i(j) - a_{l_i})\lambda & \text{if } j = l_i \text{ and } a_{l_i} \neq \infty, \\ x_i(j) + \eta_i\lambda & \text{if } j = l_i, a_{l_i} = \infty, \\ x_i(j) & \text{if } j \neq l_i, \end{cases}$$

Algorithm 2

On the basis of algorithm 1, the initial value of random feasible solution x_0 is given so that $k = 0$. If I = 1, make $x_{k+1}^* = y^*, T_{\max} = T, L_{\max} = L_{\max}, k = k + 1$.

If I = 0, then x_k^* is the global optimal solution of problem (1).

4.3. Evolutionary Planning Algorithms for Nonlinear Programming Global Optimization Problems. This section gives an improved evolutionary planning algorithm for problem (2), where the adaptation value is taken as the objective function value as follows: (Algorithm 2)

The initial value of η is 1 if $\eta_i < 10^{-4}$, then $\eta_i = 1$.

Table 1: Teaching quality evaluation form.

Teacher number	Evaluating indicator				Evaluation results
	K1	K2	K3	K4	
1	B	A	C	C	Good
2	B	B	C	B	Good
3	C	C	A	A	Secondary
4	C	B	B	C	Secondary
5	A	A	B	B	Good
6	B	C	B	C	Good
7	C	A	B	C	Secondary
8	B	B	A	C	Excellent
9	B	C	C	A	Secondary
10	A	B	B	C	Good

5. Application Examples

This paper uses data from the evaluation of the teaching quality of physical education teachers at a university, with the aim of analysing the factors affecting the quality of physical education. Table 1 shows that the indicators of teaching quality evaluation are divided into five items based on teaching effectiveness, teaching content, teaching attitudes, and teaching methods [23–25]. It is assumed here that K1: teaching attitude, K2: teaching content, K3: teaching programme, K4: teaching effectiveness, and K5: evaluation result are the data of five training samples, and the evaluation grades are A: excellent (90–100), B: good (80–90), C: moderate (70–80), D: pass (60–70), and E: fail (<60).

The information entropy of each attribute is calculated first. For K1, there are {1, 2, 6, 8, 9} (3 good, 1 moderate and 1 excellent), {3, 4, 7 (3 moderate), and {5, 10} (2 good) for the evaluation of teaching attitude. Then, the information entropy of K1 is calculated as follows:

$$
\begin{aligned}
E(K1) &= \frac{1}{5}\times\left[\frac{3.\left(5^3-3^3\right)}{(5+3)^3}+\frac{1.\left(5^3-1^3\right)}{(5+1)^3}+\frac{1.\left(5^3-1^3\right)}{(5+1)^3}\right]=0.3445,\\
E(K1) &= \frac{1}{3}\times\left[\frac{3.\left(3^3-3^3\right)}{(3+3)^3}\right]=0,\\
E(K1) &= \frac{1}{2}\times\left[\frac{2.\left(2^3-2^3\right)}{(2+2)^3}\right]
\end{aligned}
\tag{7}
$$

The information entropy of the teaching attitude K1 is

$$E(K1)=\frac{5}{10}.0.3445+\frac{3}{10}.0+\frac{2}{10}.0=0.1772. \tag{8}$$

Similarly, we obtain the information entropy of other attributes:

$$E(K2)=0.2947, E(K3)=0.2486, E(K4)=0.2433. \tag{9}$$

Comparing the entropy of each attribute, the ranking is E(K1)<E(K4)<E(K3)<E(K2), so K1 is chosen as the root node and three branches are created, A, B, and C. According to the flow of the algorithm, the test attributes are selected in turn under the branches and nodes are created until the end of the sample division [26].

Based on the decision tree created in Figure 1, we can see that each branch represents the combined set of attributes tested, and the whole decision tree represents the combined destructions.

It is clear from this analysis that teaching attitude is the most important aspect of teaching. When the teaching attitude is excellent, the result of teaching evaluation is good; when the teaching attitude is medium, the result of teaching evaluation is medium; when the teaching attitude is good, the result of teaching evaluation also depends on the teaching programme, but the teaching attitude is still the dominant factor [27, 28].

Evaluation of physical education teaching in universities is ranked. After the calculation of the autonomous evaluation method to obtain the results so that $b=2$, we can get the dominant weight vector ω = 0.4546, 0.2908, 0.1637, 0.0726 to get the ideal order of ranking as

$$u_1 \underset{0.9891}{\succ} u_2 \underset{0.8971}{\succ} u_8 \underset{0.5283}{\succ} u_4 \underset{0.0.7272}{\succ} u_5 \underset{0.8306}{\succ} u_3 \underset{0.5542}{\succ} u_6 \underset{0.6636}{\succ} u_7 \underset{0.5464}{\succ} u_9 \underset{0.7277}{\succ} u_{10}. \tag{10}$$

The results, e.g. $u_8 \underset{0.5283}{\succ} u_4$, do not mean that u_8 is definitely better than u_4, u_4 still has a 04717 probability of being better than u_8, and this form of conclusion is not suitable for making absolute judgements of superiority between some of the evaluated objects at the intersection of competencies. This form of evaluation gives the most reliable ranking of superiority between objects, but at the same time accommodates a variety of possible rankings (e.g. $u_8 \underset{0.5283}{\succ} u_4$ is equivalent to $u_4 \underset{0.4717}{\succ} u_8$).

This form of evaluation allows multiple absolute evaluation findings to be embedded in a single probabilistic evaluation finding, avoiding the subjective assumptions caused by the “multiple evaluation findings nonconsistency phenomenon” [23–25].

Table 2 shows the parameter settings for the numerical calculations, while Tables 3 and 4 show the results of the numerical calculations.

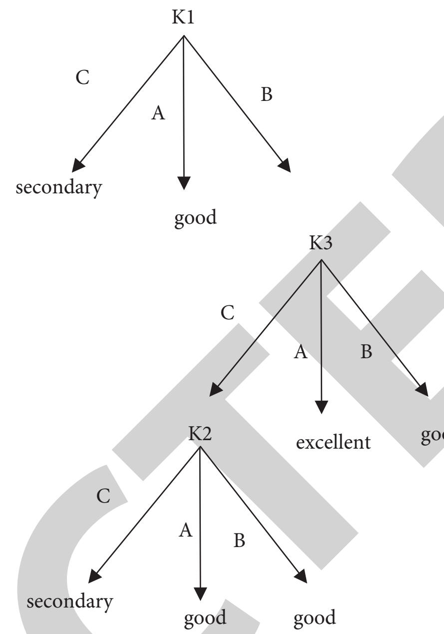

Figure 1: Evaluation decision tree.

Table 2: Parameter setting values for the simulated annealing algorithm.

T_{max}	T_{min}	δ	L_{max}	d	α	β
11	0.001	0.974	3	1	1	1.02

Table 3: Calculation results based on the simulated annealing algorithm and penalty function method proposed in the paper.

Functions	Optimal solution	Worst value	Average best value
Paper method	−10.945	−10.874	−10.912
Penalty function method	−10.401	−10.271	−10.397

Table 4: Calculation results based on the evolutionary planning algorithm and penalty function method in this paper.

Functions	Evolutionary algebra	Population size	Optimal solution	Worst value	Average best value
Paper method	1000	10	−10.967	−10.875	−10.926
Penalty function method	1000	10	−10.567	−10.156	−10.478

6. Conclusions

In this paper, we address the problem of the absolute nature of the evaluation of the merits of traditional physical education classrooms and the inconsistency of the findings of multiple evaluations, and construct a method to evaluate the merits of the evaluated students by highlighting their own strengths. The validity of the method is verified by calculation, and the evaluation conclusion with probability information is obtained.

Data Availability

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

Conflicts of Interest

The authors declare that they have no conflicts of interest regarding this work.

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