An Evaluation Model of the Learning Effect of Physical Education Major Courses in Colleges

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Abstract—There are several problems with the evaluation of the learning effect of physical education (PE) major courses in colleges, namely, the diversity of constraints and the lack of multiple perspectives. To solve the problems, this paper puts forward a novel model to evaluate the said learning effect. Firstly, the authors identified the problems and principles of learning effect evaluation of PE major courses in colleges, and established an evaluation index system from the perspectives of teachers and students. On this basis, an effective evaluation algorithm was developed to quantify the learning effect through gray clustering analysis. The proposed evaluation model can accurately assess the learning effect of PE major courses. The research findings enjoy great significance in theoretical innovation and engineering application.

Keywords—Physical education (PE), colleges, evaluation system, evaluation algorithm

1 Introduction

Physical education (PE) is an essential part of higher education. High-quality PE helps college students develop in an all-round way [1-3]. Currently, various modern techniques and concepts have been applied to higher education, reshaping the contents, forms, means and modes of PE in colleges [4-6].

Many scholars have explored deep into the implementation of PE in colleges. For instance, Kwon & Block [7] discussed how to educate PE teachers with the adapted PE e-learning program. Egan et al. [8] carried out a case study of a health-friendly PE program, which covers various physical activities in school. Packham & Street [9] investigated the effects of PE on student fitness, achievement and behavior. Heemskerk et al. [10] analyzed how the intensity and cognitive demand of PE courses on subsequent learning. The above studies mainly focus on strategic analysis, failing to evaluate the learning effect of PE major courses in colleges. To improve subsequent learning of PE, the learning effect of the said courses must be evaluated in a systematic and reasonable manner, and the weaknesses of PE in colleges must be identified and solved, making PE in colleges more efficient and effective.

It is a complex and systematic task of decision-making to evaluate the learning effect of PE major courses in colleges. Many kinds of influencing factors must be pro-
trusted before making the correct decisions [11-12]. The traditional methods for sys-
tematic decision-making include analytic hierarchy process (AHP) [13-14], decision
tree [15-16], Bayesian method [17-18] and Markov model [19-20]. However, these
traditional methods only apply to specific scopes, and have limitations in fuzzy deci-
sion-making.

Drawing on multiple intelligence theory and grey correlation theory [21-27], this
paper probes deep into the evaluation system for the learning effect of PE major
courses in colleges, and established an effective gray clustering evaluation algorithm
to evaluate the said effect.

The remainder of this paper is organized as follows: Section 2 enumerates the
problems and principles of the learning effect evaluation of PE major courses in col-
eges; Section 3 sets up an evaluation system for the said learning effect from multiple
perspectives; Section 4 designs and implements an evaluation algorithm for the said
learning effect; Section 5 puts forward the research conclusions.

2 Preliminaries

2.1 Existing problems

In higher education, the PE is an important means to implement quality education.
More and more departments and majors have opened PE major courses. Meanwhile, a
growing attention has been paid to the learning effect of PE major courses and its
evaluation. However, it is very difficult to implement the existing evaluation methods,
because various problems have emerged in the evaluation process. The current prob-
lems mainly fall into five categories:

- **First**, there is no unified implementation standard for PE among colleges. Each
college has its own way to open and teach PE major courses. Thus, the evaluation
standard of learning effect must be diversified.
- **Second**, the modes and contents of PE major courses vary from college to college,
owing to the different understandings of the role of PE in higher education. Each
college administrator looks at the learning effect from a unique perspective.
- **Third**, the current evaluation systems mostly focus on one or a few indices, rather
than evaluate the learning effect comprehensively from multiple levels. In other
words, there is not yet an organic and comprehensive evaluation system.
- **Fourth**, many colleges lag behind the times in the modes, methods, means and
contents of PE, failing to introduce emerging techniques into the teaching process.
Therefore, the learning effect evaluation is generally outdated and static.
- **Fifth**, the indices are not scientific and rational enough in the evaluation models
for the learning effect. These models cannot demonstrate the objectives of PE ma-
jor, the requirements of quality education, integration between the theories and
practices in PE. There is ample room to improve the effectiveness, accuracy and re-
liability of the current models.
2.2 Evaluation principles

To make the evaluation more effective and feasible, the above problems can be resolved by the following principles:

1. Diversification:

Traditionally, the learning effect of PE major courses in colleges is evaluated by a single subject or from only one perspective. The evaluation model lacks clarity and adaptiveness. The evaluation results often deviate from the actual situation.

To solve the problem, multiple perspectives should be introduced to diversify the evaluation process. Besides learning, the relevant links like teaching should be taken into account. In addition to PE classes, such environments as extracurricular activities should be considered.

Moreover, the evaluation contents ought to be diversified. To reflect the requirements of quality education, the evaluation model should not only consider the contents taught in PE classes, but also the PE contents relevant to quality education. The multiple intelligence theory should be adopted to improve the current model.

Finally, the evaluation subjects must also be diversified. It is improper to evaluate the learning effect by a single subject. Instead, many other subjects, namely, college administrators, PE teachers, students and social organizations, should be involved to output holistic and consistent results.

2. Contemporaneity:

The objectives and emphases of higher education change constantly with the times. Higher education has been evolving dynamically, carrying contemporary features. At present, the main objective of higher education has changed from helping students to pass exams to enhancing their overall quality. The PE major courses are opened to advance the quality education of college students.

Against this backdrop, the evaluation model should adapt to the current situation of higher education: the pursuit of quality education. The following aspects should be covered in the evaluation: individualized teaching, teaching reform, integration between theories and practices, and expansion of teaching methods/means.

3. Scientificity:

The learning effect of PE major courses in colleges must be evaluated in a scientific manner. The scientificity is a generalized concept, rather than the scientific nature of logic and systemic evaluation indices. In addition to clear scientific meanings, the evaluation indices should be objective, comprehensive, pertinent and effective.

To ensure their objectivity, the evaluation indices must be selected from the actual situation of PE in colleges, revealing the nature of learning effect. Next, the indices should be chosen in the light of comprehensiveness, ensuring the consistency of evaluation results. The pertinence of the evaluation indices cannot be achieved simply by listing all types of indices. The exhaustion method would create many redundant indices, suppressing the evaluation accuracy. Instead, the indices should be selected from multiple angles, considering the evaluation objectives. Finally, the selected indices should quantify the learning effect in an effective manner, and generate correct and reliable results.
3 Evaluation System

Under the above principles, this paper attempts to construct a novel evaluation system for the learning effect of PE major courses in colleges from multiple perspectives. There are two types of subjects in the system: the teaching subjects and the learning subjects. Thus, evaluation system can be split into two parts: the teacher-based subsystem and the learner-based subsystem.

3.1 Teacher-based subsystem

The teacher-based subsystem evaluates the learning effect from the perspectives of administrators and PE teachers in colleges. Based on multiple intelligence theory, these subjects examine the impacts of the following factors of PE major on PE education and student learning: resource provision, curriculum planning, classroom teaching, practical teaching, and teaching reform.

Among them, resource provision reflects the quality of software/hardware and the ability of faculty/staff in PE major; curriculum planning manifests the logic and systemic level of PE major courses; classroom teaching demonstrates how well the basic knowledge of PE major is imparted to students; practical teaching measures the integration between classroom knowledge and practical training; teaching reform reveals the innovation ability in PE. The teacher-based subsystem (Table 1) was established based on these factors.

| Criterion layer               | Index layer               | Meaning                                                        |
|-------------------------------|---------------------------|----------------------------------------------------------------|
| Resource provision            | Software/hardware quality | The promoting effects on education quality and learning effect  |
|                               | Teacher ability           |                                                                 |
|                               | Administrator ability     |                                                                 |
| Curriculum planning           | Rationality of major courses | The promoting effects on musical rhythmic and logical intelligences |
|                               | Progress control          |                                                                 |
|                               | Teaching contents         |                                                                 |
| Classroom teaching            | Teaching method           | The promoting effects on linguistic, musical rhythmic, logical, spatial and bodily intelligences |
|                               | Teaching means            |                                                                 |
|                               | Teaching attitude         |                                                                 |
|                               | Professional skills       |                                                                 |
| Practical learning            | Innovation ability        | The promoting effects on musical rhythmic, logical, spatial, bodily, intrapersonal and interpersonal intelligences |
|                               | Thinking ability          |                                                                 |
|                               | Social service            |                                                                 |
|                               | Theory-practice integration |                                                                 |
|                               | Coordination              |                                                                 |
| Teaching reform               | Reform ability            | The promoting effects on logical, intrapersonal, interpersonal and naturalist intelligences |
|                               | PE participation          |                                                                 |
|                               | Theory implementation     |                                                                 |
3.2 Student-based subsystem

The student-based subsystem evaluates the learning effect from the perspectives of PE majors in colleges. Based on multiple intelligence theory, the learning effect of PE major courses was evaluated by the following abilities of PE majors: digestive ability, creativity, practical ability and output.

Specifically, digestive ability reflects the digestion of knowledge before, during and after class, and how the digestion affects the learning effect; creativity measures the innovation and development of students in the course of PE, and how these elements affect the learning effect; practical ability demonstrates how well the students integrates theories and practices and how the integration affects the learning effect; output refers to the performance of the students after receiving the PE major courses. The student-based subsystem (Table 2) was established based on these factors.

Table 2. Student-based subsystem

| Criterion layer | Index layer | Meaning |
|-----------------|-------------|---------|
| Digestive ability | Digestion of basic knowledge | The effects on linguistic, musical rhythmic, logical, and naturalist intelligences |
|                  | Acceptance of professional moves | |
|                  | Acquisition of professional skills | |
|                  | Correctness of learning attitude | |
|                  | Dedication to learning | |
| Creativity | Innovation and development | The effects on musical rhythmic, logical, and naturalist intelligences |
|              | Thinking ability | |
|              | Observation ability | |
| Practical ability | Participation in sports activities | The effects on bodily, logical, intrapersonal, spatial and naturalist intelligences |
|                 | Satisfaction of social service | |
|                 | Physical function and health | |
|                 | Teamwork ability | |
| Output | Pass rate of major courses | The quantified output of students and its impacts on overall quality |
|         | Excellent rate of major courses | |
|         | Failure rate of major courses | |
|         | Participation rate of sports competitions | |
|         | Number of sports competition winners | |
|         | Number of students engaged in PE research | |
|         | Number of published PE papers authored by students | |
|         | Number of attendees in domestic/international PE academic exchanges | |

4 Evaluation Algorithm

4.1 Index processing

From the above two subsystems, it can be seen that the criterion layer contains two types of indices, namely, benefit indices and cost indices. The quality of a benefit
index is positively correlated with its value, while that of a cost index is negatively correlated with its value.

To unify the evaluation standard for different perspectives, the two types of indices were normalized as follows. Let \( n \) be the number of evaluation indices, and \( V_i \) be the value of the i-th evaluation index \( r_i \) of an object.

1. **Processing of benefit indices**

   If a benefit index is qualitative and can be described by fuzzy membership, its value can be expressed as a fuzzy membership function \( \psi(r) \):

   \[
   V_i = \psi(r)
   \]

   (1)

   If a benefit index is qualitative and can be described by a fuzzy interval number (i.e. the initial value is \( u_i = [u_i^a, u_i^b], u_i^a \leq u_i^b \)), its value can be normalized as:

   \[
   V_i = [v_i^a, v_i^b] = \left[ \frac{u_i^a - \inf(u_i)}{\sup(u_i) - \inf(u_i)}, \frac{u_i^b - \inf(u_i)}{\sup(u_i) - \inf(u_i)} \right],
   0 \leq v_i^a \leq v_i^b \leq 1
   \]

   (2)

   where, \( \inf(u_i) \) and \( \sup(u_i) \) are the lower and upper limits of the i-th evaluation index \( r_i \), respectively.

   If a benefit index is quantitative with an actual value of \( u_i \), its value can be normalized as:

   \[
   V_i = \frac{u_i - \inf(u_i)}{\sup(u_i) - \inf(u_i)}, \quad 0 \leq V_i \leq 1
   \]

   (3)

   where, \( \inf(u_i) \) and \( \sup(u_i) \) are the lower and upper limits of the i-th evaluation index \( r_i \), respectively.

2. **Processing of cost indices**

   If a cost index is qualitative and can be described by fuzzy membership, its value can be expressed as a fuzzy membership function \( \psi(r) \):

   \[
   V_i = 1 - \psi(r)
   \]

   (4)

   If a cost index is qualitative and can be described by a fuzzy interval number (i.e. the initial value is \( u_i = [u_i^a, u_i^b], u_i^a \leq u_i^b \)), its value can be normalized as:

   \[
   V_i = [v_i^a, v_i^b] = \left[ \frac{\sup(u_i^a) - u_i^b}{\sup(u_i^b) - \inf(u_i^a)}, \frac{\sup(u_i^b) - u_i^b}{\sup(u_i^b) - \inf(u_i^a)} \right],
   0 \leq v_i^a \leq v_i^b \leq 1
   \]

   (5)
If a benefit index is quantitative with an actual value of $u_i$, its value can be normalized as:

$$v_i = \frac{\text{sup}(u_i) - u_i}{\text{sup}(u_i) - \text{inf}(u_i)}, \quad 0 \leq v_i \leq 1$$

(6)

### 4.2 Levels of evaluation indices

To clarify the evaluation results, the score of each evaluation index was divided into different levels. The number of levels should be controlled in a rational interval. Otherwise, the evaluation results will become vague and fuzzy.

After consulting education experts, scholars and college administrators, the authors decided to divide the score of each evaluation index into seven levels, namely, unacceptable, inadequate, adequate, fair, good, very good and excellent, according to the abovementioned principles. The seven levels constitute a 0-1 scale, as shown in Table 3.

| Levels     | Symbols | Intervals |
|------------|---------|-----------|
| Unacceptable | L_A     | 0-0.4     |
| Inadequate  | L_B     | 0.4-0.5   |
| Adequate    | L_C     | 0.5-0.6   |
| Fair        | L_D     | 0.6-0.7   |
| Good        | L_E     | 0.7-0.8   |
| Very good   | L_F     | 0.8-0.9   |
| Excellent   | L_G     | 0.9-1.0   |

### 4.3 Algorithm implementation

This paper introduces gray clustering analysis to evaluate the learning effect of PE major courses in colleges. Before the gray clustering analysis, the whitening weight function should be set up corresponding to each level of evaluation results. The whitening weight function, the key to the gray clustering analysis, is a continuous function that changes continuously with the independent variable.

The effectiveness of evaluation relies on the following conditions: the whitening weight function must fall on the same level as the membership of the target index; the whitening weight functions corresponding to non-adjacent indices should not intersect each other; there must be a unique point whose membership is one in the whitening weight functions on all seven levels, and the functions on both sides of the point are monotonic.

For these reasons, if the learning effect is unacceptable, the lower limit form of the whitening weight function was adopted (Fig. 1):
Fig. 1. The lower limit form of the whitening weight function for the unacceptable learning effect

The corresponding calculation model can be expressed as:

\[
\begin{align*}
  f^{LA}(v) &= \begin{cases} 
  0 & v_i \in \left[0, \frac{v_{LA} + v_{LA}}{2}, 1\right] \\
  \frac{v_{LB} + v_{LA} - 2v_i}{2(v_{LB} - v_{LA})} & v_i \in \left[0, \frac{v_{LA} + v_{LA}}{2}\right] \\
  \frac{1.5v_{LB} - v_i}{v_{LA}} & v_i \in \left[\frac{v_{LA}}{2}, v_{LA}\right] \\
  1 & v_i \in \left[0, \frac{v_{LA}}{2}\right]
  \end{cases}
\]
\]

(7)

If the learning effect is excellent, the upper limit form of the whitening weight function was adopted (Fig. 2):

Fig. 2. The upper limit form of the whitening weight function for the excellent learning effect
The corresponding calculation model can be expressed as:

\[
f^{LG}(v_i) = \begin{cases} 
1 & v_i \in \left[ \frac{v_{LE} + 1}{2}, 1 \right] \\
\frac{v_i + 0.5 - 1.5 \cdot v_{LE}}{1 - v_{LE}} - \frac{v_i - 0.5 \cdot (v_{LF} + v_{LE})}{v_{LF} - v_{LE}} & v_i \in \left[ \frac{v_{LF} + 1}{2}, 1 \right] \\
0 & v_i \in \left[ 0, \frac{v_{LF} + v_{LE}}{2} \right]
\end{cases}
\] (8)

For learning effects on the other levels \( L_d \leq L_j \leq L_F \), the whitening weight function was expressed in triangular form (Fig. 3):

Fig. 3. The triangular form of the whitening weight functions for learning effects on the other levels

The corresponding calculation model can be expressed as:
Considering the various index weights and multiple perspectives, the weighted synthetic fuzzy membership of the learning effect can be expressed as:

$$f^L_i(v_i) = \begin{cases} 
    v_i - 0.5 \left( v_{iL(j-1)} + v_{iL(j-2)} \right) & v_i \in \left[ \frac{v_{iL(j-2)} + v_{iL(j-1)}}{2}, \frac{v_{iL(j-1)}}{2} \right] \\
    v_i + 0.5v_{ij} - 1.5v_{iL(j-1)} & v_i \in \left[ \frac{v_{iL(j-1)}}{2}, \frac{v_{iL(j-1)} + v_{iL(j-2)}}{2} \right] \\
    1.5v_{ij} - 0.5v_{iL(j-0)} - v_i & v_i \in \left[ \frac{v_{iL(j-2)} + v_{iL(j-1)}}{2}, \frac{v_{iL(j-1)}}{2} \right] \\
    0.5 \left( v_{iL(j-1)} + v_{iL(j-0)} \right) - v_i & v_i \in \left[ \frac{v_{iL(j-1)}}{2}, \frac{v_{iL(j-1)} + v_{iL(j-2)}}{2} \right]
\end{cases}
$$

(9)

$$\phi_j = w_a \cdot \sum_{i=1}^{\tilde{n}} (w_j \cdot f_a^L_i(v_i)) + w_b \cdot \sum_{i=1}^{\tilde{n}} (w_j \cdot f_b^L_i(v_i))$$

(10)

where, $w_a$ and $w_b$ are the weights from the perspectives of teachers and students, respectively; $f_a^L_i(v_i)$ and $f_b^L_i(v_i)$ are the fuzzy memberships when the index membership falls on level $L_j$ from the perspectives of teachers and students, respectively.

Formula (10) provides the weighted synthetic fuzzy membership of each object, which determines the evaluation level of the object.

5 Conclusion

This paper firstly analyzes the problems in learning effect evaluation of PE major courses in colleges, and puts forward the principles for index selection. Drawing on multiple intelligence theory, an evaluation index system for the said learning effect was established from the perspectives of teachers and students. Then, a fuzzy evaluation algorithm was developed based on the gray clustering analysis, aiming to effectively quantify the learning effect. The proposed evaluation model involves both theoretical innovation and algorithm implementation, providing a highly operable and feasible method for evaluation of complex systems.

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Article submitted 2020-02-11. Resubmitted 2020-03-14. Final acceptance 2020-03-14. Final version published as submitted by the authors.