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Research Article

Analysis of Educational Quality in University Courses Utilizing Process Assessment

Yuhao Zhang[1], Jiashuang Sun[2], Xiaoran Ma[3]
[1]*College of Artificial Intelligence, Tianjin University of Science and Technology, 300222, China*
[2]*College of Art and Design, Tianjin University of Science and Technology, 300222, China*
[3]*College of Economics and Management, Tianjin University of Science and Technology, 300222, China*

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ABSTRACT

The progressive integration of formative assessment into university education has led to its widespread adoption for evaluating students' daily learning behaviors and conditions. This paper leverages data on classroom learning experiences from a specific university, utilizing machine learning, K-means clustering, the TOPSIS evaluation model, and the entropy weighting method. The study aims to explore the correlation between formative assessment and the quality of university student learning, ultimately developing an evaluation model. This model identifies key factors influencing student learning attitudes, supporting the use of formative assessment in higher education.

1. Introduction

With the ongoing reform of educational systems, process assessment has gained significant traction among universities. Unlike outcome assessments, process assessments provide a more comprehensive evaluation of students' learning attitudes and conditions [1].

In process assessments, students' learning attitudes are influenced by both external environments and internal motivations [2]. This study examines the factors impacting students' learning attitudes, constructs a mathematical model for evaluating learning styles, and develops an evaluation model to reflect students' enthusiasm for learning.

This paper is structured as follows: Section 2 analyzes the data and factors influencing students' learning attitudes. Section 3 introduces the evaluation model construction. Section 4 discusses the model's results. Section 5 summarizes the paper's main findings.

2. *Data* Analysis

The data collected include student numbers, colleges, classes, course codes, class codes, teacher codes, test names, test times, test full scores, student scores, and normalized scores. Students select different courses within the core basic curriculum, with some choosing multiple courses and others selecting only one. Not all students participate in every test, and different teachers may not post pre-class tests consistently.

To identify the factors most impacting students' learning attitudes, various control variables are explored. The following sections examine the influence of college factors, the number of courses selected by students, student attendance rates, and the roles of major, class, course, teacher, and classroom on learning attitudes.

Corresponding author's E-mail: a15839176622@163.com URL: www.tust.edu.cn

2.1. College factor

The average scores of students in different colleges are calculated and summarized, yielding the average and variance of scores for each college. The data are visualized in Fig. 1.

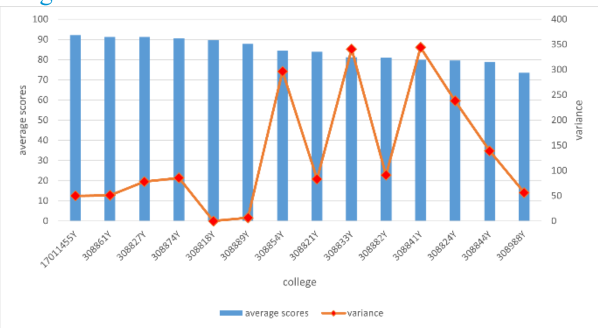

Fig.1 College factor visualization

The scores and their stability vary across colleges, indicating differences in learning atmospheres and, consequently, student attitudes. Thus, college factors influence students' learning attitudes.

2.2. Number of courses taken

We calculate the average of each student's normalized scores across tests as their representative score. The number of courses selected by each student is categorized, and their representative scores are visualized in Fig. 2.

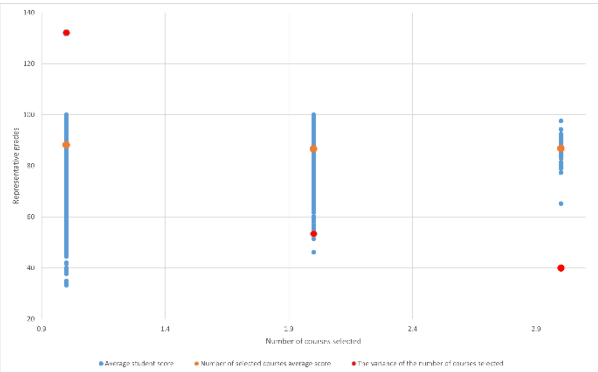

Fig.2 Number of Selected Courses

As shown from Fig. 2, students' scores tend to stabilize and improve with the number of courses selected, suggesting that more courses correlate with higher enthusiasm and better attitudes.

2.3. Student attendance

To determine the attendance rates, we calculated the ratio of attended tests to the total number of tests available for each course. This allowed us to assess the correlation between attendance and student performance. Fig. 3 and Fig. 4 illustrate the relationships between attendance rates and the representative scores.

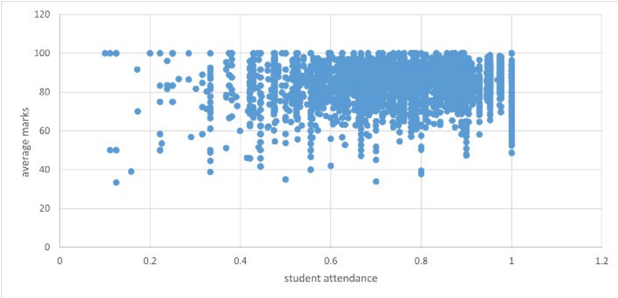

Fig.3 Scatter plot of attendance

Count the number of people with scores greater than 80 in each attendance range and draw a bar chart, which is shown in Fig. 4.

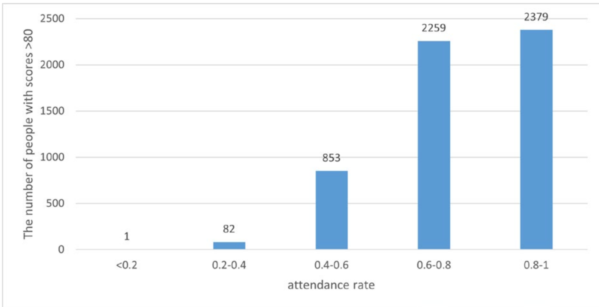

Fig.4 attendance and high score statistics

As can be seen from Fig. 3 and Fig. 4, Higher attendance rates were found to correlate strongly with better scores. Students who attended more classes tended to achieve higher grades, indicating that regular attendance positively impacts learning attitudes and overall academic performance. This correlation highlights the importance of consistent participation in classes for academic success.

2.4. Major, class, curriculum, teacher factor

We calculated the average grades and their variances for each major, class, curriculum, and teacher. Our analysis showed the following:

Major: While the major a student belongs to does influence learning attitudes, the effect is relatively minor compared to other factors.

Class: The class a student is in significantly impacts their learning attitude. Different classes exhibited varying levels of enthusiasm and performance, indicating that the class environment plays a crucial role in shaping student attitudes.

Curriculum: The specific courses students take also affect their overall performance and attitude towards learning. Certain courses are associated with higher engagement and better outcomes.

Teacher: The influence of the teacher on student performance and stability is noteworthy. Different teaching styles and methods can lead to varying levels of student engagement and success.

This comprehensive analysis indicates that class environment and teaching quality are substantial determinants of students' learning attitudes and performance.

3. Construction of Evaluation Model

We aggregated data for all students within each college and class to calculate the average test scores, test participation rates, and the number of courses taken by students in each group. This process yielded a dataset that includes the college (or class), average test score, average test participation rate, and number of courses taken. Given the limited number of indicators, we employed the TOPSIS method for evaluation [3].

3.1. Data standardization

As attendance, GPA, and the average number of courses taken are all positive indicators, the dataset—comprising college (or class), average test score, average test participation rate, and number of courses taken—was standardized accordingly.

3.2. Calculate index weight

To ensure the index weights are both objective and scientifically valid, we used the entropy weight method combined with the analytic hierarchy process. The resulting weights are displayed in Fig. 5.

	attendance rate	grade	Average number of courses selected
College weight	0.24935	0.3984	0.35225
Class weight	0.28405	0.3831	0.33285

Fig.5 index weight

3.3. Calculating the score

To calculate the scores, we first define Z^+ as the maximum value for each column in the vector matrix and Z^- as the minimum value for each column. The distance of the i-th evaluation object to the maximum value is given by:

$$D_i^+ = \sqrt{\sum_{j=1}^{m} \omega_j \left(Z_j^+ - z_{ij}\right)^2} \tag{1}$$

Similarly, the distance of the i-th evaluation object to the minimum value is defined as:

$$D_i^- = \sqrt{\sum_{j=1}^{m} \omega_j \left(Z_j^- - z_{ij}\right)^2} \tag{2}$$

Next, the unnormalized score for the i-th evaluation object is calculated using the formula:

$$S_i = \frac{D_i^-}{D_i^+ + D_i^-} \tag{3}$$

In this equation, $0 \leq S_i \leq 1$, and a larger S_i corresponds to a smaller D_i^+, indicating that the evaluation object is closer to the maximum value. By applying the indicator weights to the sample distance calculations, we determine the final score for each sample [3].

4. Introduction of Result

Using the constructed model, MATLAB calculations yield the final results. The evaluation hierarchy is shown in Fig. 6.

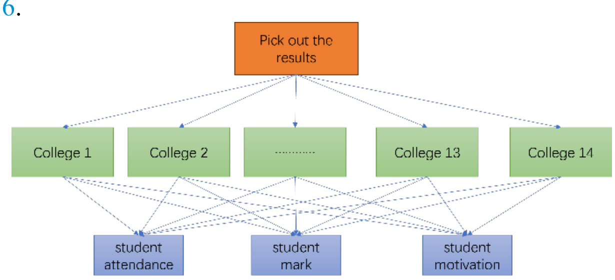

Fig.6 evaluation hierarchy diagram

4.1. Personal evaluation model

Students are clustered using K-Means into better and worse groups, which are then evaluated by TOPSIS based on attendance rates, courses selected, and individual performance [2].

5. Conclusion

This study constructs a process evaluation model based on students' routine performances, identifies factors influencing learning attitudes, and highlights well-performing classes, colleges, and students. The findings will assist universities in enhancing process assessment practices.

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Authors Introduction

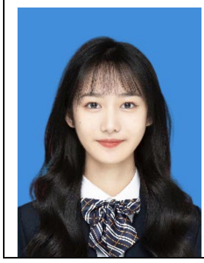
Mr. Yuhao Zhang

He is an undergraduate majoring in artificial intelligence at Tianjin University of Science and Technology. He learns about electronic information and artificial intelligence, and currently focuses on digital image processing, deep learning and pose estimation.

Ms. Jiashuang Sun

She is an undergraduate majoring in visual communication design in Tianjin University of Science and Technology. She studies all kinds of graphic design and artificial intelligence AIGC, and currently focuses on brand image design and artificial intelligence AIGC.

Ms. Xiaoran Ma



She is an undergraduate majoring in Public Administration at Tianjin University of Science and Technology. She studies administration and public service management, and currently focuses on research in administrative management and public policy.