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Research on the Assessment System of Computational Mechanics Courses Based on the TOPSIS Entropy Weight Model

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Abstract: This paper takes the assessment and evaluation of computational mechanics course as the background, and constructs a diversified course evaluation system that is student-centered and integrates both quantitative and qualitative evaluation methods. The system not only pays attention to students' practical operation and theoretical knowledge mastery but also puts special emphasis on the cultivation of students' innovative abilities. In order to realize a comprehensive and objective evaluation, the assessment and evaluation method of the entropy weight model combining TOPSIS (Technique for Order Preference by Similarity to Ideal Solution) multi-attribute decision analysis and entropy weight theory is adopted, and its validity and practicability are verified through example analysis. This method can not only comprehensively and objectively evaluate students' learning outcomes, but also provide a scientific decision-making basis for curriculum teaching reform. The implementation of this diversified course evaluation system can better reflect the comprehensive ability of students and promote the continuous improvement of teaching quality.

Keywords: TOPSIS entropy weight model; Computational mechanics; Course assessment and evaluation system; Assessment model

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1. Introduction

With the rapid evolution of the global industrial landscape, industrial software is facing unprecedented opportunities and challenges in the new industrial trend of intelligence, greening, and integration. Accelerating the independent innovation of industrial software is not only of great significance to enhance the core competitiveness of the manufacturing industry but also the key to safeguarding the security of the industrial supply chain and promoting the high-quality development of the industry. However, the current development of China's industrial software is still subject to a number of key technical constraints, is listed as one of the 35 “bottleneck” technologies; the national “14th Five-Year Plan” clearly emphasizes the independent development of key basic software, particularly to address and overcome “bottleneck” technologies, in which computational mechanics plays an important role. It not only provides the core algorithm and theoretical foundation for industrial software but also is the key to promoting the development of industrial software and enhancing its accuracy and application scope. Therefore, strengthening the research and application of computational mechanics is of great significance for the independent innovation of China’s industrial software.

Computational mechanics is an emerging cross-disciplinary discipline that involves mechanics, computational science, computational mathematics, and other disciplines according to the relevant theories and methods in mechanics, and utilizes modern electronic computers and a variety of numerical methods to solve complex problems and practical problems in mechanics [1]. In the context of the digital transformation of the manufacturing industry, the importance of computational mechanics is becoming increasingly prominent, and the social demand for practical simulation engineers is becoming more and more urgent. Integrating the content of computational mechanics into undergraduate teaching can not only enable students to have a more comprehensive understanding of the development and application of mechanics but also stimulate their interest in learning and enhance their practical and innovative abilities. By combining traditional engineering mechanics theory with computer technology, it is possible to construct approximate models and apply computational mechanics to produce accurate analytical results. This process not only helps students to understand the application of computational mechanics in real engineering but also improves their problem-solving skills and prepares them to apply the research results in engineering practice in the future [2].

However, how to scientifically evaluate the learning effectiveness of students in computational mechanics courses has become an urgent problem for educators. Reform of the course assessment method is an important part of the teaching reform in colleges and universities and is one of the important factors affecting the quality of teaching [3,4]. Through the course assessment evaluation, not only can we understand the level of knowledge mastery of the students and the level of practical skills, but also can understand the students’ total performance in the class, which is conducive to the timely adjustment of the teaching method and pay attention to the middle- and lower-level students to help them better complete their studies. Traditional methods of course assessment, such as written tests or experimental operations, although they can reflect students’ knowledge and skills to a certain extent, it is often difficult to comprehensively and objectively evaluate students’ comprehensive performance. Therefore, it is particularly important to explore more scientific and reasonable methods of course assessment and evaluation.

Currently, in university teaching management practices, methods like principal component analysis, factor analysis, hierarchical analysis, and fuzzy evaluation are primarily used for course assessment. However, these methods often lack scientific rigor and fairness when it comes to assessing and ranking student performance.

The Analytic Hierarchy Process (AHP) is an indirect decision-making method that focuses on qualitative analysis and judgment based on the evaluator’s understanding of the essence and elements of the evaluation problem. However, when confronted with many analysis indicators, the data becomes complex, and determining weights becomes challenging. As a result, AHP tends to rely more on qualitative analysis, making it relatively weak in quantitative data, which can undermine its persuasiveness to some extent. Fuzzy evaluation [5,6] uses precise numerical methods to process evaluation subjects with inherent fuzziness. This approach allows for a scientific, reasonable, and realistic quantification of information containing ambiguity. It is widely used in areas such as ecological optimization [7], low-carbon economic development analysis [8], and real estate investment risk assessment [9]. However, the computational process of fuzzy comprehensive evaluation is relatively complex, and there is considerable subjectivity in determining the weight vector for the indicators. This can lead to what is known as the "over-fuzziness" phenomenon, especially when dealing with large indicator sets, making it difficult to distinguish degrees of membership among evaluation subjects. Factor analysis [10,11] is a statistical technique designed to extract common factors from a large number of variables, aiming to reveal underlying relationships by reducing the number of variables. This method is used to verify hypotheses about relationships among variables. Yet, when calculating factor scores, the least squares method used can fail under certain circumstances. Additionally, the meaning of the extracted factors may not be entirely clear, and some information may be lost, affecting the accuracy of the analysis. Principal component analysis (PCA) [12,13] aims to transform multiple indicators into a smaller number of composite indicators (i.e., principal components) using a dimension reduction approach. Each principal component captures most of the information from the original variables, with no redundancy among them, resulting in a more scientific and effective analysis. However, the interpretation of principal components can often be somewhat ambiguous, as their meaning may not be as clear-cut as that of the original variables. This is an unavoidable trade-off in the process of dimensionality reduction.

All of the aforementioned evaluation methods are subject to varying degrees of human interference, making the exploration of scientific and reasonable course assessment approaches increasingly important. In recent years, the multi-attribute decision-making analysis method based on TOPSIS (Technique for Order Preference by Similarity to Ideal Solution) has garnered attention from educators due to its ability to consider multiple evaluation indicators and rank them based on their respective weights. This approach has become especially popular when combined with entropy weight theory, as it can more objectively determine the weight of each evaluation indicator, leading to more scientific and rational assessment results.

In light of this, this paper proposes a course assessment method based on the TOPSIS entropy weight model. The aim is to evaluate student learning outcomes more scientifically by employing a comprehensive approach that combines multiple evaluation indicators with an objective method for determining weights. Applying this method not only helps to thoroughly and objectively assess students' overall abilities and learning achievements but also provides valuable references and a basis for decision-making in course curriculum reform.

2. The construction of the assessment and evaluation system for the course of computational mechanics

The computational mechanics course has constructed a student-centered curriculum that integrates both quantitative and qualitative assessment methods. It not only emphasizes practical skills and theoretical knowledge but also places significant emphasis on fostering students' innovation abilities within a diverse evaluation framework. Within this assessment system, there is a strong emphasis on the student's agency, rather than the traditional teacher-centric approach. Students are not only the objects of evaluation but also the subjects, a design aimed at fostering a sense of self-responsibility toward learning, enhancing confidence, increasing motivation, and improving self-monitoring skills. The theoretical framework is illustrated in **Figure 1**.

2.1. Establishment of evaluation criteria

The assessment system has revolutionized the traditional evaluation criteria for computational mechanics courses. It deeply integrates the course's teaching objectives with the goals of cultivating engineering mechanics professionals, aligning with the knowledge and skills required in engineering mechanics as outlined in professional development objectives. Drawing from this, the course's teaching objectives are designed to establish a set of clear evaluation criteria for computational mechanics courses that meet the requirements of engineering mechanics professional training. This standard not only prioritizes student development but also aids in achieving the training objectives of engineering mechanics professionals, ensuring a high degree of alignment between teachers' teaching objectives and students' learning objectives.

2.2. Reform of evaluation modalities

Reforming the traditional summative assessment of students, this approach adopts a formative assessment model that is process-oriented, continuous, and staged, facilitating an ongoing assessment process throughout teaching and learning. By establishing online platforms for documenting students' developmental progress, teachers can systematically collect and preserve students' learning materials, thereby gaining a comprehensive understanding of students' developmental changes. Additionally, teachers assess students' comprehension and application of course knowledge through staged practical assignments and provide feedback on students' learning outcomes through classroom presentations and discussions, thereby promoting students' progress in the subsequent stages of learning.

2.3. Diversification of evaluation content, methods, and subjects

As illustrated in **Figure 1**, regarding the evaluation content, this system not only focuses on students' grasp of theoretical knowledge such as "Fundamental Theory of Computational Mechanics" and "Relevant Mathematics and Physics Knowledge," but also emphasizes practical skills, application of computational tools, innovation capabilities, and overall qualities such as "Fostering Innovation," "Problem-Solving and Computational Abilities," and "Teamwork and Communication Skills." As for evaluation methods, a combination of quantitative and qualitative approaches is employed. Quantitative evaluation includes exam scores, completion of assignments and exercises, etc., to objectively assess students' mastery of foundational knowledge and skills. Qualitative evaluation, on the other hand, assesses students' learning attitudes, practical skills, innovation capabilities, and overall qualities through classroom performance, project completion, self-assessment, peer assessment, and other means. This combination of quantitative and qualitative evaluation methods enables a more comprehensive assessment of student performance, ensuring the objectivity and accuracy of the evaluation results. In terms of evaluation subjects, with the introduction of diverse evaluation subjects such as self-assessment and peer assessment, the traditional model of having teachers as the sole evaluators is challenged. This ensures the objectivity and fairness of the evaluation results while also stimulating students' interest and motivation in learning.

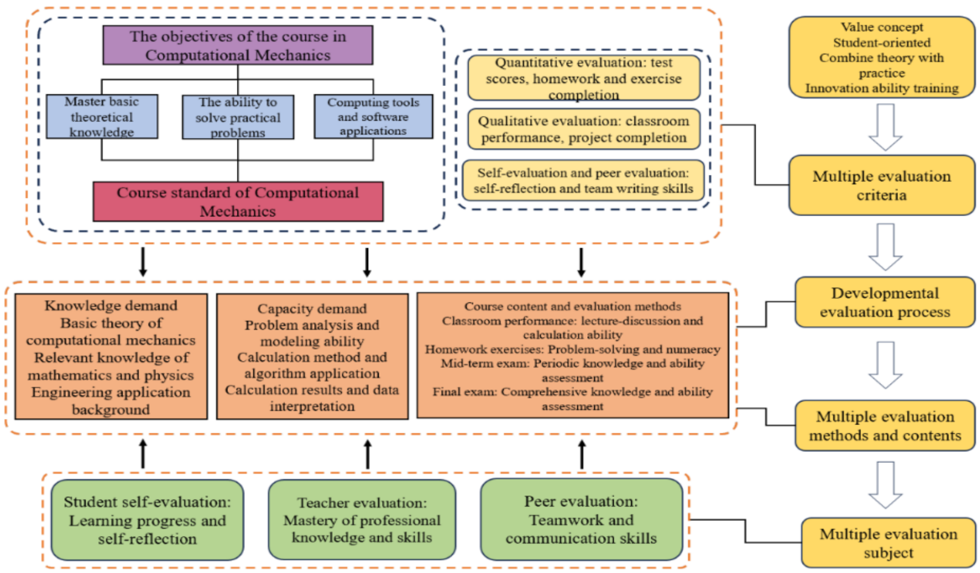

Figure 1. Construction diagram of assessment and evaluation system of computational mechanics course

2.4. Digital diversity full cycle appraisal

To comprehensively assess students' academic performance and practical application skills, a multidimensional evaluation matrix has been constructed, taking into account various aspects such as students' learning achievements, classroom participation, homework completion, and laboratory skills. Through a digitized, diversified, and continuous assessment process, as illustrated in **Figure 2**, real-time feedback is provided to students to better guide their learning and progress. The specific distribution of assessments includes online knowledge learning (5%), tests and assignments (5%), participation assessment (10%), online interaction (10%), project design and implementation (20%), lab reports (10%), and mid-term and final projects (40%).

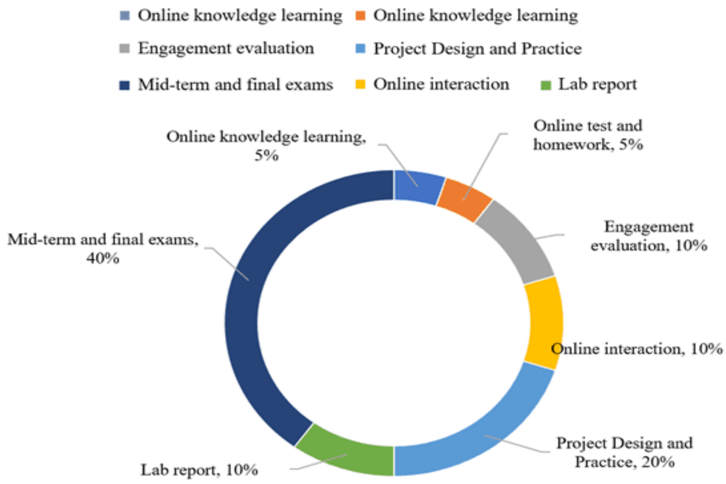

Figure 2. Digital diversity full cycle appraisal weighting

In summary, the assessment system of the computational mechanics course achieves a comprehensive, objective, and fair evaluation of students through the diversification of evaluation content, the variety of evaluation methods, and the diversity of evaluation subjects. This not only promotes students' overall development but also provides strong feedback and support for teachers' teaching, driving continuous improvement in teaching quality.

3. Assessment evaluation of computational mechanics course assessment based on TOPSIS entropy weight modeling

3.1. Fundamentals of the TOPSIS entropy weight modeling

TOPSIS is a multi-attribute decision-making analysis method that entails ranking evaluation objects by computing their distances from the positive ideal solution and negative ideal solution. Entropy weight theory, on the other hand, determines the weights of each attribute based on information entropy, objectively reflecting the importance of attributes in the evaluation process. This paper combines TOPSIS with entropy weight theory to construct a comprehensive evaluation model.

Let the set of multi-attribute decision schemes be $D = \{d_1, d_2, \ldots, d_m\}$, its merits and demerits are measured through a series of attribute variables $x_1, x_2, \ldots, x_n$. The n attribute values of any solution $d_i(i=1, 2, \ldots, m)$ form a vector $[a_{i1}, a_{i2}, \ldots, a_{in}]$ in an n-dimensional space, uniquely identifying and characterizing the solution d_i. The positive ideal solution is a hypothetical optimal solution whose attribute values are taken from the best values in the decision matrix. Conversely, the negative ideal solution represents a virtual solution where all attributes are at their worst. By computing and comparing the distances between each solution and these two ideal solutions, the optimal choices within the solution set can be determined.

It is worth noting that the introduction of the concepts of positive and negative ideal solutions in TOPSIS is primarily aimed at addressing situations where multiple solutions are equidistant from the positive ideal solution. By further calculating the distances between these solutions and the negative ideal solution, more effective differentiation can be achieved. This strategy not only enhances the discriminative power of TOPSIS but also strengthens the scientific and precise nature of its decision-making.

The steps of the TOPSIS entropy weight analysis method are shown in **Figure 3**.

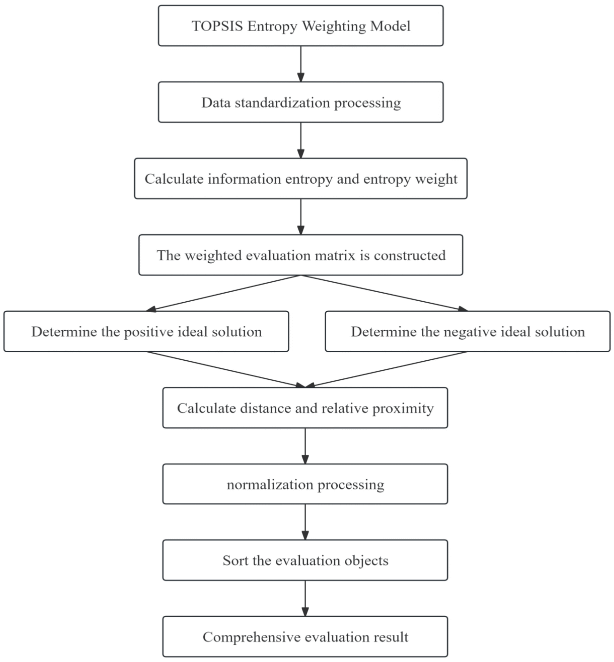

Figure 3. TOPSIS entropy weight analysis method

(1) Indicator standardization: The raw evaluation data are standardized to form a standardized matrix containing m samples and n indicators. The standardization method uses the extreme value standardization method, and for positive and negative indicators, the formulas: $x_{ij}' = \frac{x_{ij} - min_i(x_{ij})}{max_j(x_{ij}) - min_j(x_{ij})}$ and $x_{ij}' = \frac{max_j(x_{ij}) - x_{ij}}{max_j(x_{ij}) - min_j(x_{ij})}$ are used, respectively.

where x_{ij} is an element in the initial matrix, x_{ij}' is a normalized element, and $max_j(x_{ij})$ and $min_j(x_{ij})$are the maximum and minimum values of indicator j, respectively.

(2) Determination of indicator weights: Based on the standardization matrix, the information entropy and the coefficient of variation of the evaluation indicators are calculated, and then the weight of each indicator is determined. The formula for calculating information entropy is: $E_j = -\frac{1}{ln\, m}\sum_{i=1}^{m} p_{ij}\, ln\, p_{ij}$

where p_{ij} is the proportion of elements in the normalized matrix. The coefficient of variation is then calculated based on the degree of variability of the indicator, and the larger its value, the larger the weight. Finally, the information entropy weights of the defined indicators are: $\omega_j = \frac{1-E_j}{\sum_{j-1}^{n}(1-E_j)}$:

(3) Calculation of the weighted normalized matrix: The weights of the indicators are multiplied with the

normalized evaluation matrix to obtain the weighted normalized matrix, i.e.: $V = (v_{ij})=(\omega_j \cdot x'_{ij})$

(4) Determination of the positive and negative ideal solutions: The positive ideal solution and negative ideal solution are the maximum and minimum value vectors in the weighted normalized matrix, respectively, i.e: $V^+ = \left(\max_i v_{i1}, \max_i v_{i2}, \ldots, \max_i v_{im}\right)$, $V^- = \left(\min_i v_{i1}, \min_i v_{i2}, \ldots, \min_i v_{im}\right)$

(5) Calculation of the distance between the evaluation object and the ideal solution: The Euclidean distance method is used to calculate the distance from the indicator vector of each evaluation object to the positive and negative ideal solutions, i.e: $S_i^+ = \sqrt{\sum_{j=1}^{n} (v_{ij} - v_j^+)^2}$, $S_i^- = \sqrt{\sum_{j=1}^{n} (v_{ij} - v_j^-)^2}$

(6) Calculation of the comprehensive evaluation value: The comprehensive status of the evaluation object reflected by the positive and negative distances is combined, the comprehensive evaluation index of each evaluation object is calculated, and it is expanded by 100 times as the comprehensive score, i.e.: $C = \frac{K}{K^2 + K^2} \times 100$

where the larger the value of C_i, the closer the evaluator is to the ideal value and the better the performance.

3.2. Assessment and evaluation process of computational mechanics course based on TOPSIS entropy weight modeling

In order to verify the effectiveness of the TOPSIS-based entropy weight model in the assessment and evaluation of computational mechanics courses, this paper takes the computational mechanics course at our university as an example for empirical analysis.

For data sources and pre-processing, we gathered diverse data from students, encompassing various dimensions such as academic performance, classroom participation, homework completion, and laboratory skills (all sourced from actual course records and student performance). To mitigate dimensional and unit differences among different metrics, we standardized the raw data, transforming it into dimensionless numerical values, and facilitating subsequent analysis and computation.

Table 1 presents the raw score sheet for the computational mechanics course. This score sheet comprises the various components that constitute the final grade, as determined by the instructor through a comprehensive digital assessment set up throughout the entire course period. The specific weightings for each component of the total grade are detailed in **Figure 2**, depicting the breakdown of students' overall grade composition.

Table 1. Students' raw grades in computational mechanics course

Number	Name	Online knowledge learning	Online tests and assignments	Engagement evaluation	Online interaction	Project design and practice	Experimental report	Midterm and final exams	Total score	Ranking
1	student1	38	95	75	74	90	64	88	81.15	8
2	student2	73	99	42	73	47	89	63	63.6	37
3	student3	44	97	91	84	79	62	45	64.55	34
4	student4	67	59	96	40	71	100	41	60.5	47
5	student5	32	73	34	55	76	87	56	60.45	48
6	student6	46	44	60	64	73	90	47	59.3	53
7	student7	95	89	38	54	37	67	79	64.1	35
8	student8	44	30	75	90	79	49	92	77.7	12
9	student9	77	36	39	64	72	65	89	72.45	23

Table 1 (Continued)

Number	Name	Online knowledge learning	Online tests and assignments	Engagement evaluation	Online interaction	Project design and practice	Experimental report	Midterm and final exams	Total score	Ranking
10	student10	77	50	70	88	74	47	84	75.25	18
11	student11	35	30	88	42	74	98	95	78.85	11
12	student12	64	42	42	69	80	84	56	63.2	40
13	student13	92	36	64	30	82	45	44	54.3	58
14	student14	61	72	41	94	36	34	75	60.75	45
15	student15	89	43	90	39	39	81	91	71.8	25
16	student16	35	37	31	46	56	53	43	45	65
17	student17	33	63	98	98	50	76	99	81.6	7
18	student18	60	92	83	65	57	97	40	59.5	52
19	student19	77	49	91	42	93	88	54	68.6	29
20	student20	48	94	62	83	90	75	33	60.3	49
21	student21	31	85	48	65	47	75	48	53.2	61
22	student22	78	32	93	88	98	30	56	68.6	29
23	student23	47	99	92	98	48	57	56	64	36
24	student24	74	42	41	58	90	33	97	75.8	15
25	student25	39	73	53	39	83	46	82	68.8	28
26	student26	100	99	75	66	81	46	76	75.25	18
27	student27	75	52	100	50	95	38	94	81.75	6
28	student28	46	52	79	65	66	73	90	75.8	15
29	student29	39	43	52	46	43	71	60	53.6	60
30	student30	60	87	72	57	88	88	72	75.45	17
31	student31	92	76	72	87	100	63	91	87	2
32	student32	56	35	82	39	30	78	73	59.65	51
33	student33	67	58	87	60	61	39	57	59.85	50
34	student34	79	34	46	30	59	31	77	58.95	54
35	student35	97	89	44	41	94	59	96	80.9	9
36	student36	75	85	39	94	38	75	68	63.6	37
37	student37	98	92	42	61	85	44	32	54	59
38	student38	76	100	67	79	99	92	92	89.2	1
39	student39	86	83	66	33	85	63	70	69.65	26
40	student40	53	86	81	37	84	99	87	80.25	10
41	student41	84	91	79	68	56	45	45	57.15	56
42	student42	93	98	78	83	41	92	83	76.25	14
43	student43	88	97	46	41	60	38	30	45.75	64
44	student44	84	63	88	37	35	37	81	62.95	42
45	student45	41	63	65	40	96	36	75	68.5	31
46	student46	63	44	84	72	48	76	97	76.95	13
47	student47	65	69	47	80	89	30	52	61	44

Table 1 (Continued)

Number	Name	Online knowledge learning	Online tests and assignments	Engagement evaluation	Online interaction	Project design and practice	Experimental report	Midterm and final exams	Total score	Ranking
48	student48	86	77	84	79	57	81	74	73.55	22
49	student49	63	45	60	66	80	82	46	60.6	46
50	student50	74	98	68	85	79	76	88	82.5	4
51	student51	72	53	47	53	78	100	48	61.05	43
52	student52	91	55	93	76	87	39	51	65.9	33
53	student53	91	60	52	36	91	36	73	67.35	32
54	student54	73	42	99	54	93	44	77	74.85	20
55	student55	50	64	80	84	73	44	43	58.3	55
56	student56	51	65	76	78	40	39	47	51.9	63
57	student57	91	52	58	79	35	50	55	54.85	57
58	student58	95	42	82	67	78	38	55	63.15	41
59	student59	76	58	50	71	97	96	96	86.2	3
60	student60	36	42	99	90	51	46	37	52.4	62
61	student61	56	85	31	49	86	48	66	63.45	39
62	student62	77	49	78	89	56	67	84	74.5	21
63	student63	48	54	69	86	94	93	83	81.9	5
64	student64	35	72	64	94	34	84	89	71.95	24
65	student65	38	40	72	30	85	74	76	68.9	27

Based on the obtained raw score data and the basic steps of TOPSIS entropy weight analysis, the raw data is standardized. Since student scores are all positive indicators, the positive indicator extreme value normalization method is employed for standardization. This yields a standardized matrix of 65×7, as shown in **Table 2**, where index 1 represents online knowledge learning, index 2 represents online tests and assignments, and so forth in a similar manner.

Table 2. Standardized matrix

	index1	index2	index3	index4	index5	index6	index7
object1	38	95	75	74	90	64	88
object2	73	99	42	73	47	89	63
object3	44	97	91	84	79	62	45
object4	67	59	96	40	71	100	41
object5	32	73	34	55	76	87	56
object6	46	44	60	64	73	90	47
object7	95	89	38	54	37	67	79
object8	44	30	75	90	79	49	92
object9	77	36	39	64	72	65	89
object10	77	50	70	88	74	47	84
object11	35	30	88	42	74	98	95

Table 2 (Continued)

	index1	index2	index3	index4	index5	index6	index7
object12	64	42	42	69	80	84	56
object13	92	36	64	30	82	45	44
object14	61	72	41	94	36	34	75
object15	89	43	90	39	39	81	91
object16	35	37	31	46	56	53	43
object17	33	63	98	98	50	76	99
object18	60	92	83	65	57	97	40
object19	77	49	91	42	93	88	54
object20	48	94	62	83	90	75	33
object21	31	85	48	65	47	75	48
object22	78	32	93	88	98	30	56
object23	47	99	92	98	48	57	56
object24	74	42	41	58	90	33	97
object25	39	73	53	39	83	46	82
object26	100	99	75	66	81	46	76
object27	75	52	100	50	95	38	94
object28	46	52	79	65	66	73	90
object29	39	43	52	46	43	71	60
object30	60	87	72	57	88	88	72
object31	92	76	72	87	100	63	91
object32	56	35	82	39	30	78	73
object33	67	58	87	60	61	39	57
object34	79	34	46	30	59	31	77
object35	97	89	44	41	94	59	96
object36	75	85	39	94	38	75	68
object37	98	92	42	61	85	44	32
object38	76	100	67	79	99	92	92
object39	86	83	66	33	85	63	70
object40	53	86	81	37	84	99	87
object41	84	91	79	68	56	45	45
object42	93	98	78	83	41	92	83
object43	88	97	46	41	60	38	30
object44	84	63	88	37	35	37	81
object45	41	63	65	40	96	36	75
object46	63	44	84	72	48	76	97
object47	65	69	47	80	89	30	52
object48	86	77	84	79	57	81	74

Table 2 (Continued)

	index1	index2	index3	index4	index5	index6	index7
object49	63	45	60	66	80	82	46
object50	74	98	68	85	79	76	88
object51	72	53	47	53	78	100	48
object52	91	55	93	76	87	39	51
object53	91	60	52	36	91	36	73
object54	73	42	99	54	93	44	77
object55	50	64	80	84	73	44	43
object56	51	65	76	78	40	39	47
object57	91	52	58	79	35	50	55
object58	95	42	82	67	78	38	55
object59	76	58	50	71	97	96	96
object60	36	42	99	90	51	46	37
object61	56	85	31	49	86	48	66
object62	77	49	78	89	56	67	84
object63	48	54	69	86	94	93	83
object64	35	72	64	94	34	84	89
object65	38	40	72	30	85	74	76

3.3. Entropy weight calculation and weighted evaluation matrix construction

Based on the standardized data, we calculate the information entropy and entropy weights for each evaluation indicator. Through entropy weight calculation, we obtain the weights of each attribute in the evaluation process, objectively reflecting their contribution to the overall evaluation. From **Table 3**, which shows the weights of various indicators in student grades, it can be observed that the weights assigned to the constituent indicators of student grades are relatively balanced. This indicates that they all play a significant role in evaluating students' overall performance. Subsequently, the obtained entropy weights are multiplied element-wise with the standardized data to construct a weighted evaluation matrix. This matrix comprehensively considers the weights of various evaluation indicators and students' actual performance, laying the foundation for subsequent TOPSIS analysis, ensuring the scientificity and accuracy of the evaluation process, and enabling a comprehensive assessment of students' overall performance from multiple perspectives.

Table 3. Weights of indicators of the components of student achievement

	index1	index2	index3	index4	index5	index6	index7
Information entropy	0.064432593	0.06429238	0.064523081	0.064433892	0.064496848	0.064285999	0.064533511
Coefficient of difference	0.935567407	0.93570762	0.935476919	0.935566108	0.935503152	0.935714001	0.935466489
Information entropy weight	0.142856492	0.142877902	0.142842675	0.142856293	0.14284668	0.142878876	0.142841082

3.4. TOPSIS analysis and ranking

Based on the weighted evaluation matrix, TOPSIS analysis is conducted. Firstly, the positive and negative ideal solutions for each evaluation indicator are determined, representing the optimal and worst values for each attribute among all evaluation objects (as shown in **Table 4**). Subsequently, the distances between each evaluation object and the positive and negative ideal solutions are calculated (detailed in **Table 5**). To obtain a more comprehensive evaluation result, the relative closeness of each evaluation object is further calculated (as presented in **Table 6**). This relative closeness reflects the similarity between the evaluation object and the ideal solution. The higher the relative closeness, the closer the evaluation object is to the ideal solution, indicating a better comprehensive evaluation result. Finally, all evaluation objects are ranked based on their relative closeness to obtain the comprehensive evaluation result. Additionally, to visually represent the data characteristics, scatter plots (as shown in **Figure 4**) are utilized to intuitively display the distance relationships between each evaluation object and the positive and negative ideal solutions.

This analytical approach not only provides a scientific basis for ranking but also assists us in comprehensively and objectively evaluating the overall performance of each evaluation object.

Table 4. Positive and negative ideal solutions for each evaluation indicator

	index1	index2	index3	index4	index5	index6	index7
Positive ideal solution	14.28564917	14.28779016	14.28426748	13.99991676	14.28466804	14.2878876	14.14126712
Negative ideal solution	4.428551244	4.286337049	4.428122918	4.285688804	4.285400411	4.286366279	4.285232462

Table 5. Distance from positive and negative ideal solutions for each evaluation object

	Positive distance	Negative distance		Positive distance	Negative distance
object1	11.59450194	18.21968015	object34	19.82819581	10.68598026
object2	13.51011628	16.509795	object35	12.96845898	18.85476875
object3	12.95413767	17.39367036	object36	14.29693625	16.07068698
object4	14.53676259	16.39100878	object37	16.06760775	16.0615246
object5	16.99388653	13.19094838	object38	6.60824809	21.69911251
object6	15.8699194	12.90200938	object39	13.01568312	16.1511162
object7	15.24152052	15.66344189	object40	11.85615305	18.67864174
object8	15.53007882	15.84971346	object41	13.96416877	15.25597301
object9	15.39391192	14.17190104	object42	9.649312194	20.33462336
object10	12.56837905	15.99802133	object43	18.36269339	13.5895486
object11	16.35213135	17.01950477	object44	16.9084197	14.19259559
object12	15.23280438	13.52801965	object45	16.98029623	13.44755338
object13	18.32532834	12.75385841	object46	13.34137144	16.11251562
object14	17.39698824	13.50508584	object47	16.00361691	13.84884234
object15	15.0491928	16.5968127	object48	9.232589043	17.90580019
object16	21.63698746	5.881543266	object49	14.67396619	13.43637263
object17	13.50598148	18.88843027	object50	7.838769501	19.56076335

Table 5 (Continued)

	Positive distance	Negative distance		Positive distance	Negative distance
object18	13.07738489	16.86306434	object51	14.92251153	14.65533335
object19	13.22125591	16.98118259	object52	13.4271744	16.87577343
object20	13.91584532	16.77586134	object53	16.08842557	14.69568118
object21	17.38675036	12.10355581	object54	14.07036697	16.58623969
object22	15.65730129	17.33189415	object55	15.2485616	13.58838229
object23	13.75864297	17.54969338	object56	17.27757171	11.44985506
object24	16.73051586	14.96489877	object57	16.39500541	12.98657798
object25	16.68096137	12.97288878	object58	14.9417672	15.11993069
object26	10.55266386	19.02047983	object59	10.69330703	19.1938579
object27	13.64924827	18.04961058	object60	18.45380928	13.65617491
object28	13.33751429	14.9708702	object61	16.48227503	13.37620266
object29	18.94613719	8.66642662	object62	11.90579465	16.36774999
object30	10.35168779	17.49211004	object63	11.30860795	18.24930036
object31	7.796399972	20.44204302	object64	15.00499513	16.52354262
object32	18.08504901	12.35921464	object65	17.07298337	13.48192926
object33	15.3017034	12.68639811			

Table 6. Comprehensive evaluation results and ranking of evaluation targets

Evaluate object	Relative proximity	Normalized score	Ranking	Raw ranking
object1	0.611107831	0.018216136	11	8
object2	0.549961485	0.016393462	23	37
object3	0.573144207	0.017084501	15	34
object4	0.529977042	0.015797758	27	47
object5	0.437005815	0.013026436	56	48
object6	0.448423513	0.013366779	49	53
object7	0.50682611	0.015107666	35	35
object8	0.505093001	0.015056005	36	12
object9	0.479334056	0.014288173	40	23
object10	0.560029304	0.016693567	20	18
object11	0.509999111	0.015202248	34	11
object12	0.470362728	0.014020752	45	40
object13	0.410366543	0.012232363	60	58
object14	0.43702846	0.013027111	55	45
object15	0.524452058	0.015633067	31	25
object16	0.21373028	0.006370954	65	65

Table 6 (Continued)

Evaluate object	Relative proximity	Normalized score	Ranking	Raw ranking
object17	0.58307681	0.017380576	13	7
object18	0.563220151	0.016788681	17	52
object19	0.562245416	0.016759626	18	29
object20	0.546592652	0.016293042	25	49
object21	0.410424895	0.012234102	59	61
object22	0.525380929	0.015660755	30	29
object23	0.560543786	0.016708903	19	36
object24	0.472147121	0.014073942	43	15
object25	0.437477384	0.013040493	54	28
object26	0.643167329	0.019171777	6	18
object27	0.569408844	0.016973156	16	6
object28	0.528849331	0.015764143	29	15
object29	0.313858093	0.009355602	64	60
object30	0.62822285	0.018726307	8	17
object31	0.723908291	0.021578535	2	2
object32	0.405962016	0.012101071	61	51
object33	0.453278266	0.013511492	48	50
object34	0.350197241	0.010438813	63	54
object35	0.592484487	0.017661004	12	9
object36	0.529204635	0.015774734	28	37
object37	0.499905333	0.014901369	38	59
object38	0.766553718	0.022849726	1	1
object39	0.553750037	0.016506393	22	26
object40	0.611716629	0.018234283	10	10
object41	0.522104688	0.015563096	33	56
object42	0.678183934	0.020215566	4	14
object43	0.42530814	0.012677747	57	64
object44	0.456338658	0.013602717	47	42
object45	0.441948858	0.01317378	52	31
object46	0.547042079	0.016306439	24	13
object47	0.463909597	0.013828394	46	44
object48	0.659795983	0.019667451	5	22
object49	0.477986862	0.014248015	41	46
object50	0.713908644	0.021280461	3	4
object51	0.495483474	0.014769561	39	43

Table 6 (Continued)

Evaluate object	Relative proximity	Normalized score	Ranking	Raw ranking
object52	0.556902039	0.016600349	21	33
object53	0.47737884	0.014229891	42	32
object54	0.541033125	0.016127322	26	20
object55	0.471214368	0.014046138	44	55
object56	0.398568767	0.01188069	62	63
object57	0.441997213	0.013175222	51	57
object58	0.502963297	0.014992522	37	41
object59	0.642210726	0.019143263	7	3
object60	0.425293729	0.012677318	58	62
object61	0.447986759	0.01335376	50	39
object62	0.578906897	0.017256278	14	21
object63	0.617408382	0.018403945	9	5
object64	0.524082111	0.01562204	32	24
object65	0.44123606	0.013152533	53	27

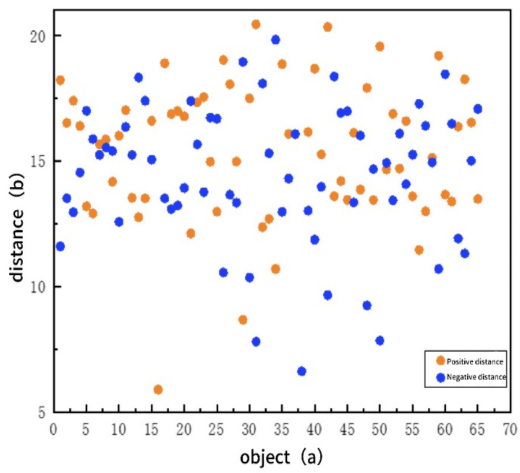

Figure 4. Scatterplot of each object with positive and negative ideal solutions

3.5. Analysis and discussion of results

Through example analysis, the effectiveness and accuracy of the TOPSIS entropy weight model are further validated. Taking point 38 as an example, it is evident from the scatter plot that its positive distance is very close to the x-axis, while the negative distance is relatively distant. This characteristic suggests that the object represented by point 38 is a relatively optimal solution in the overall evaluation. Further comparing points 15 and 12, although the positive distances of these two points are similar to the distance from the axis, indicating their similar performance in some aspects, the negative distance of point 12 is closer to the axis compared to point 15. This implies that in the consideration of comprehensive evaluation, object 15 is superior to object 12.

Through this series of analyses, it has been confirmed that the assessment method for the computational mechanics course, based on the TOPSIS entropy weight model, can comprehensively and objectively evaluate students' learning outcomes. Compared to traditional single-score evaluation methods, this approach takes into account diverse evaluation factors, more accurately reflecting students' actual abilities and comprehensive performance while effectively avoiding interference from subjective factors. Furthermore, this evaluation system can be flexibly adjusted based on different attributes and weights, making the evaluation results more scientifically and reasonably grounded.

In the instance analysis, some interesting phenomena were also observed. Following the application of the TOPSIS entropy weight analysis method, significant changes occurred in the rankings of most students. Particularly noteworthy were those students whose exam scores were not outstanding; however, due to their exceptional performance in classroom interactions, the quality of assignments completed, and laboratory skills, they achieved higher rankings in the comprehensive evaluation. This indicates that the method can effectively tap into students' potential and strengths, providing solid support for their all-round development.

4. Conclusions and outlook

This paper, focusing on the assessment of the computational mechanics course, establishes a diversified course evaluation system centered around students, integrating both quantitative and qualitative assessment methods. This system not only assesses students' practical skills and theoretical knowledge but also places particular emphasis on fostering students' innovative abilities.

The assessment method for the computational mechanics course, based on the TOPSIS entropy weight model, overcomes the limitations of traditional evaluation methods such as principal component analysis, factor analysis, analytic hierarchy process, and fuzzy comprehensive averaging. It provides a more scientific and rational evaluation and analysis of course assessments. Through example analysis, its effectiveness and practicality have been validated. This method not only comprehensively and objectively evaluates students' learning outcomes but also serves as a scientific basis for curriculum teaching reform decisions.

In the future, we will further refine the course evaluation model, exploring additional methods and technologies suitable for assessing computational mechanics courses, with the aim of serving students' growth and development better.

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