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# The Role of Student Feedback in Teaching Quality Evaluation for International Chinese Education: A Comprehensive Evaluation Approach Using Forest HyperSoft Set and TreeSoft Sets

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**Abstract**: The role of student feedback in teaching quality evaluation has gained increasing importance in the context of international Chinese education. As educational institutions strive to enhance the learning experience, student input serves as a crucial tool for assessing teaching effectiveness, curriculum design, and instructional methods. This study explores the significance of student feedback in evaluating teaching quality, focusing on its impact on pedagogical improvements, course adjustments, and overall student engagement. By analyzing various feedback mechanisms, such as course evaluations, peer assessments, and digital feedback platforms, this research highlights the advantages and challenges of integrating student perspectives into educational quality assurance. This research uses the multi-criteria decision-making (MCDM) methodology to deal with different criteria. This study uses two MCDM methods such as CIMAS and weighted product method (WPM). The CIMAS method is used to compute the criteria weights, and the WPM is used to rank the alternatives. We use the Forest HyperSoft Set to divide each main criterion into TreeSoft Set. This study divides the criteria into five TreeSoft Sets.

**Keywords**: Forest HyperSoft Set; Student Feedback; International Chinese Education; Teaching Quality.

## 1. Introduction

The globalization of education has led to an increasing number of students enrolling in international Chinese language programs. As the demand for high-quality instruction rises, educational institutions must develop systematic approaches to evaluate and improve teaching quality. One of the most effective ways to achieve this is through student feedback, which provides valuable insights into teaching effectiveness, learning experiences, and curriculum relevance. By incorporating student perspectives into quality assessment frameworks, universities can refine teaching methodologies and better address learner needs[1], [2]. Student feedback plays a pivotal role in enhancing instructional quality by offering direct insights into classroom dynamics, teaching strategies, and student engagement levels. Unlike traditional evaluation methods that rely solely on instructor self-assessments or administrative reviews, student feedback provides a firsthand account of the learning process. When properly utilized, feedback can help educators identify strengths and weaknesses in their teaching styles, leading to more effective instructional approaches and improved student outcomes[3], [4]. One of the primary advantages of student feedback in teaching quality evaluation is its ability to foster a responsive and adaptive learning environment. In international Chinese education, where students come from diverse cultural and linguistic backgrounds, teaching strategies must be flexible to accommodate varying learning styles. By analyzing feedback, instructors can modify lesson plans, adjust pacing, and incorporate more interactive elements to enhance comprehension and engagement. This iterative process ensures that educational programs remain student-centered and continuously evolve to meet learners' expectations[5], [6]. Despite its benefits, student feedback is not without challenges. Issues such as bias, subjectivity, and inconsistent response rates can affect the reliability of feedback data. Some students may provide overly positive or negative evaluations based on personal preferences rather than objective criteria. Others may hesitate to provide honest assessments due to concerns about anonymity or potential repercussions. Addressing these challenges requires well-designed feedback mechanisms that promote fairness, confidentiality, and constructive criticism[7], [8].

The integration of technology has significantly improved the effectiveness of student feedback collection and analysis. Digital platforms, AI-driven sentiment analysis, and online surveys allow institutions to gather real-time feedback and process large datasets efficiently. These advancements enable educators to identify trends, track improvements over time, and make data-driven decisions to enhance teaching quality. Additionally, technological tools can provide instant feedback to instructors, allowing them to adjust their methods dynamically[9], [10]. A well-structured feedback system must go beyond simple rating scales and incorporate qualitative elements such as open-ended comments and peer discussions. By combining quantitative data with qualitative insights, universities can gain a holistic understanding of student experiences and implement meaningful improvements. Furthermore, establishing a feedback culture where students feel empowered to share their opinions fosters a sense of ownership and responsibility in the learning process. Considering the intricacy of assessing several open innovation criteria, multi-criteria decision-making (MCDM) techniques are crucial. Determining the relevance of a topic's effective criteria gets difficult when there are several of them. These criteria may also have a hierarchical structure. Furthermore, considering every facet of open service innovation at once may be expensive and time-consuming for a company[11]. Setting these criteria in order of importance is therefore crucial. Further complicating the matter is the possibility that a wide range of stakeholders and individuals will have differing views on the criteria. In these circumstances, MCDM techniques may be used to efficiently assess and rank the criteria. Open service innovation is influenced by several aspects, which may be evaluated and prioritized using MCDM methodologies.

## 2. MCDM Approach

This section presents the steps of the MCDM approach.

### Forest HyperSoft Set

This part shows the Forest HyperSoft Set to divide the criteria and sub criteria into a different Tree Soft set. In each Tree Soft set, we can compute the criteria weights and ranking the alternatives. The Forest HyperSoft Set is split into different levels from level 1 to level n.

Let U be a universe of discourse and K is a non-empty subset of U; A be a set of criteria. Each of the criteria has various levels.

I. Level 1 be the sub criteria values.
II. Level n be the n-sub criteria values.

We can define the Forest HyperSoft as[12]:

$$G: P\big(Forest(A)\big) \to P(K) \tag{1}$$

We apply the steps of the CIMAS method to obtain the criteria weights[13], [14].

Design the decision matrix.

Combine the decision matrix.

Compute the normalize the decision matrix

$$q_{ij} = \frac{x_{ij}}{\nabla_j}; i = 1, \dots m; j = 1, \dots, n \tag{2}$$

Where $\nabla_j$ means to the standard deviation.

Compute the weighted decision matrix

$$d_{ij} = q_{ij} v_{ij} \tag{3}$$

Where $v_{ij}$ means to the weight of experts.

Obtain the max and min values of the weighted decision matrix.

$$s_{ij}^{max} = \max_i d_{ij} \tag{4}$$

$$s_{ij}^{min} = \min_i d_{ij} \tag{5}$$

Obtain the distance between the $s_{ij}^{max}$ and $s_{ij}^{min}$

$$H_j = s_{ij}^{max} - s_{ij}^{min} \tag{6}$$

Calculate the criteria weights.

$$w_j = \frac{H_j}{\sum_{j=1}^{n} H_j} \tag{7}$$

Apply the steps of the weighted product method (WPM) to rank the alternatives[15], [16].

Compute the weighted decision matrix

$$U_{ij} = w_j * x_{ij} \tag{8}$$

Rank the alternatives. The alternatives are ranked based on product each row in the weighted decision matrix.

## 3. Case Study

This section shows the results of the Role of Student Feedback in Teaching Quality Evaluation for International Chinese Education using two MCDM methods to compute the criteria weights and ranking the alternatives. We use the Forest HyperSoft set to divide each main criteria as a Tree Soft set. Then we compute the criteria weights and rank the alternatives in each case. This study divides the criteria into five Tree as:

I. Teaching Effectiveness
  1.1 Clarity of Instruction
    a. 1.1.1 Use of Examples (High, Moderate, Low)
    b. 1.1.2 Explanation of Complex Topics (Excellent, Satisfactory, Needs Improvement)
  1.2 Teaching Methods
    c. 1.2.1 Interactive Learning (Highly Engaging, Moderately Engaging, Passive)
    d. 1.2.2 Adaptability to Student Needs (Very Adaptive, Somewhat Adaptive, Not Adaptive)
  1.3 Classroom Management
    e. 1.3.1 Time Management (Well-Managed, Average, Poor)
    f. 1.3.2 Student Engagement (High, Medium, Low)

II. Curriculum and Course Content
  2.1 Relevance of Course Materials
    a. 2.1.1 Alignment with Language Proficiency Goals (Strongly Aligned, Partially Aligned, Weakly Aligned)
    b. 2.1.2 Cultural Integration (Comprehensive, Basic, Limited)
  2.2 Difficulty Level
    c. 2.2.1 Suitability for Student Levels (Well-Suited, Somewhat Suitable, Not Suitable)
    d. 2.2.2 Progression of Content (Logical, Inconsistent, Unstructured)
  2.3 Learning Resources
    e. 2.3.1 Use of Digital Tools (Extensive, Limited, None)
    f. 2.3.2 Availability of Supplementary Materials (Comprehensive, Basic, Insufficient)

III. Student Engagement and Satisfaction

3.1 Participation in Class

a. 3.1.1 Frequency of Discussions (Frequent, Occasional, Rare)
b. 3.1.2 Interaction with Instructor (High, Moderate, Low)

3.2 Feedback Mechanism

c. 3.2.1 Responsiveness of Instructor (Highly Responsive, Somewhat Responsive, Unresponsive)
d. 3.2.2 Implementation of Student Suggestions (Frequently Implemented, Occasionally Considered, Ignored)

3.3 Satisfaction with Teaching Style

e. 3.3.1 Overall Experience (Excellent, Satisfactory, Poor)
f. 3.3.2 Comfort with Learning Pace (Fast, Balanced, Slow)

IV. Assessment and Evaluation

4.1 Fairness of Assessment

a. 4.1.1 Transparency in Grading (Very Transparent, Somewhat Transparent, Opaque)
b. 4.1.2 Diversity of Evaluation Methods (Diverse, Moderate, Limited)

4.2 Constructiveness of Feedback

c. 4.2.1 Timeliness of Feedback (Immediate, Delayed, None)
d. 4.2.2 Usefulness of Feedback (Highly Useful, Moderately Useful, Not Useful)

4.3 Self-Assessment Opportunities

e. 4.3.1 Reflection Activities (Frequent, Occasional, None)
f. 4.3.2 Student Progress Awareness (Clear Understanding, Partial Understanding, Unclear)

V. Learning Environment and Support

5.1 Classroom Atmosphere

a. 5.1.1 Inclusiveness (Highly Inclusive, Moderately Inclusive, Not Inclusive)
b. 5.1.2 Encouragement of Student Participation (Highly Encouraging, Somewhat Encouraging, Discouraging)

5.2 Instructor Support

c. 5.2.1 Availability for Consultation (Highly Available, Sometimes Available, Rarely Available)
d. 5.2.2 Approachability (Highly Approachable, Neutral, Not Approachable)

5.3 Technological Support

e. 5.3.1 Access to Online Platforms (Seamless, Some Issues, Frequent Problems)
f. 5.3.2 Effectiveness of E-Learning Tools (Highly Effective, Somewhat Effective, Ineffective)

The alternatives of this study are: Student Course Evaluation Surveys, Peer Observation and Review, Online Learning Analytics and Performance Metrics, Instructor Self-Assessment Reports, Focus Group Discussions with Students, Alumni Feedback and Career Progression Tracking, Benchmarking Against International Teaching Standards, AI-Driven Sentiment Analysis on Student Feedback.

In first TreeSoft Set.

We created the decision matrix based on the opinions of three experts. Then we combine the different decision matrix into a single matrix.

Then we compute the normalized decision matrix using Eq. (2) as shown in Table 1.

Then we compute the weighted decision matrix using Eq. (3) as shown in table 2.

Then we obtain the max and min values of the weighted decision matrix using Eqs. (4 and 5).

Then we obtain the distance between the $s_{ij}^{max}$ and $s_{ij}^{min}$ using Eq. (6).

Then we calculate the criteria weights using Eq. (7).

Table 1. The normalized decision matrix.

| | $SFC_{1111}$ | $SFC_{1121}$ | $SFC_{1211}$ | $SFC_{1221}$ | $SFC_{1311}$ | $SFC_{1321}$ |
|---|---|---|---|---|---|---|
| $A_1$ | 1.498651 | 1.267229 | 0.224676 | 0.055897 | 2.616133 | 2.439109 |
| $A_2$ | 1.628234 | 2.459363 | 0.764523 | 1.572105 | 0.14564 | 1.68828 |
| $A_3$ | 2.631298 | 2.511929 | 0.224676 | 0.055897 | 2.908763 | 0.451365 |
| $A_4$ | 0.089605 | 0.882367 | 0.952793 | 1.528319 | 1.071401 | 3.189938 |
| $A_5$ | 0.137854 | 3.216321 | 0.108177 | 3.051049 | 0.730495 | 0.937451 |
| $A_6$ | 1.163147 | 0.802015 | 1.24196 | 0.654462 | 0.906477 | 2.439109 |
| $A_7$ | 1.628234 | 0.557581 | 0.526325 | 1.830629 | 0.655382 | 1.68828 |
| $A_8$ | 2.822571 | 0.912405 | 3.176671 | 1.060181 | 0.613847 | 0.451365 |

Table 2. The weighted expert decision matrix.

| | $SFC_{1111}$ | $SFC_{1121}$ | $SFC_{1211}$ | $SFC_{1221}$ | $SFC_{1311}$ | $SFC_{1321}$ |
|---|---|---|---|---|---|---|
| $A_1$ | 0.33836 | 0.285469 | 0.026153 | 0.007896 | 0.627786 | 0.125208 |
| $A_2$ | 0.367617 | 0.55402 | 0.088992 | 0.222062 | 0.034949 | 0.086665 |
| $A_3$ | 0.594085 | 0.565862 | 0.026153 | 0.007896 | 0.698008 | 0.02317 |
| $A_4$ | 0.020231 | 0.198771 | 0.110907 | 0.215877 | 0.257101 | 0.16375 |
| $A_5$ | 0.031124 | 0.72454 | 0.012592 | 0.430965 | 0.175295 | 0.048123 |
| $A_6$ | 0.262611 | 0.18067 | 0.144566 | 0.092444 | 0.217525 | 0.125208 |
| $A_7$ | 0.367617 | 0.125606 | 0.061265 | 0.258579 | 0.15727 | 0.086665 |
| $A_8$ | 0.63727 | 0.205537 | 0.369769 | 0.149752 | 0.147303 | 0.02317 |

Apply the steps of the weighted product method (WPM) to rank the alternatives.

We compute the weighted decision matrix using Eq. (8) as shown in Table 3.

Then we rank the alternatives. The alternatives are ranked based on product each row in the weighted decision matrix.

Table 3 The weighted decision matrix.

| | $SFC_{1111}$ | $SFC_{1121}$ | $SFC_{1211}$ | $SFC_{1221}$ | $SFC_{1311}$ | $SFC_{1321}$ |
|---|---|---|---|---|---|---|
| $A_1$ | 0.0638888 | 0.048131 | 0.004593 | 0.001209 | 0.153143 | 0.004703 |
| $A_2$ | 0.069413 | 0.09341 | 0.015627 | 0.033998 | 0.008525 | 0.003255 |
| $A_3$ | 0.1121745 | 0.095406 | 0.004593 | 0.001209 | 0.170273 | 0.00087 |
| $A_4$ | 0.00382 | 0.033513 | 0.019476 | 0.033051 | 0.062717 | 0.006151 |
| $A_5$ | 0.0058769 | 0.12216 | 0.002211 | 0.065982 | 0.042762 | 0.001808 |
| $A_6$ | 0.049586 | 0.030462 | 0.025386 | 0.014153 | 0.053063 | 0.004703 |
| $A_7$ | 0.069413 | 0.021178 | 0.010758 | 0.039589 | 0.038365 | 0.003255 |
| $A_8$ | 0.1203287 | 0.034654 | 0.064933 | 0.022928 | 0.035933 | 0.00087 |

In second TreeSoft Set.

We created the decision matrix based on the opinions of three experts. Then we combine the different decision matrix into a single matrix.

Then we compute the normalized decision matrix using Eq. (2) as shown in Table 4.

Then we compute the weighted decision matrix using Eq. (3) as shown in table 5.

Then we obtain the max and min values of the weighted decision matrix using Eqs. (4 and 5).

Then we obtain the distance between the $s_{ij}^{max}$ and $s_{ij}^{min}$ using Eq. (6).

Then we calculate the criteria weights using Eq. (7).

Table 4. The normalized decision matrix.

| | $SFC_{2111}$ | $SFC_{2121}$ | $SFC_{2211}$ | $SFC_{2221}$ | $SFC_{2311}$ | $SFC_{2321}$ |
|---|---|---|---|---|---|---|
| $A_1$ | 1.543758 | 3.852906216 | 0.228261 | 0.086792 | 3.014679 | 3.320888 |
| $A_2$ | 1.12293 | 1.31997713 | 0.593901 | 2.441023 | 0.167828 | 2.298622 |
| $A_3$ | 0.383377 | 1.541955266 | 0.411081 | 0.390564 | 1.881844 | 2.298622 |
| $A_4$ | 0.328187 | 2.22770915 | 0.411081 | 1.329001 | 0.167828 | 3.320888 |
| $A_5$ | 0.157687 | 3.234538552 | 0.593901 | 0.390564 | 0.393151 | 1.276356 |
| $A_6$ | 1.128449 | 3.386752131 | 0.228261 | 1.016189 | 0.461526 | 3.320888 |
| $A_7$ | 1.691984 | 2.354553799 | 0.534723 | 2.842435 | 0.755224 | 2.298622 |
| $A_8$ | 3.228646 | 3.852906216 | 3.227357 | 1.646153 | 0.707362 | 0.614542 |

Table 5. The weighted expert decision matrix.

| | $SFC_{2111}$ | $SFC_{2121}$ | $SFC_{2211}$ | $SFC_{2221}$ | $SFC_{2311}$ | $SFC_{2321}$ |
|---|---|---|---|---|---|---|
| $A_1$ | 0.379037 | 0.534240715 | 0.033965 | 0.012291 | 0.739491 | 0.266018 |
| $A_2$ | 0.275712 | 0.183026912 | 0.088371 | 0.34568 | 0.041168 | 0.18413 |

| | | | | | | |
|---|---|---|---|---|---|---|
| **A3** | 0.09413 | 0.213806212 | 0.061168 | 0.055309 | 0.46161 | 0.18413 |
| **A4** | 0.080579 | 0.308892265 | 0.061168 | 0.188204 | 0.041168 | 0.266018 |
| **A5** | 0.038717 | 0.448498378 | 0.088371 | 0.055309 | 0.096439 | 0.102242 |
| **A6** | 0.277067 | 0.469604184 | 0.033965 | 0.143905 | 0.113211 | 0.266018 |
| **A7** | 0.415431 | 0.326480437 | 0.079566 | 0.402525 | 0.185254 | 0.18413 |
| **A8** | 0.792726 | 0.534240715 | 0.480224 | 0.233117 | 0.173514 | 0.049227 |

Apply the steps of the weighted product method (WPM) to rank the alternatives.

We compute the weighted decision matrix using Eq. (8) as shown in Table 6.

Then we rank the alternatives. The alternatives are ranked based on product each row in the weighted decision matrix.

Table 6. The weighted decision matrix.

| | SFC2111 | SFC2121 | SFC2211 | SFC2221 | SFC2311 | SFC2321 |
|---|---|---|---|---|---|---|
| **A1** | 0.068904 | 0.019916 | 0.005623 | 0.001093 | 0.158071 | 0.007108 |
| **A2** | 0.050121 | 0.006823 | 0.014631 | 0.030734 | 0.0088 | 0.00492 |
| **A3** | 0.017112 | 0.00797 | 0.010127 | 0.004917 | 0.098672 | 0.00492 |
| **A4** | 0.014648 | 0.011515 | 0.010127 | 0.016733 | 0.0088 | 0.007108 |
| **A5** | 0.007038 | 0.01672 | 0.014631 | 0.004917 | 0.020614 | 0.002732 |
| **A6** | 0.050367 | 0.017506 | 0.005623 | 0.012795 | 0.0242 | 0.007108 |
| **A7** | 0.07552 | 0.012171 | 0.013174 | 0.035788 | 0.039599 | 0.00492 |
| **A8** | 0.144107 | 0.019916 | 0.07951 | 0.020726 | 0.03709 | 0.001315 |

In third TreeSoft Set.

We created the decision matrix based on the opinions of three experts. Then we combine the different decision matrix into a single matrix.

Then we compute the normalized decision matrix using Eq. (2) as shown in Table 7.

Then we compute the weighted decision matrix using Eq. (3) as shown in table 8.

Then we obtain the max and min values of the weighted decision matrix using Eqs. (4 and 5).

Then we obtain the distance between the $s_{ij}^{max}$ and $s_{ij}^{min}$ using Eq. (6).

Then we calculate the criteria weights using Eq. (7).

Table 7. The normalized decision matrix.

| | SFC3111 | SFC3121 | SFC3211 | SFC3221 | SFC3311 | SFC3321 |
|---|---|---|---|---|---|---|
| **A1** | 2.200672 | 1.684017 | 0.255249 | 0.073272 | 3.394414 | 0.588523 |
| **A2** | 2.210871 | 2.449933 | 0.597944 | 1.398272 | 0.139976 | 0.950827 |

| | | | | | | |
|---|---|---|---|---|---|---|
| $A_3$ | 0.069937 | 3.532693 | 0.635758 | 0.735772 | 2.097888 | 0.851856 |
| $A_4$ | 2.509559 | 0.059876 | 1.082444 | 2.535207 | 0.995578 | 2.277036 |
| $A_5$ | 1.025737 | 2.613095 | 1.00965 | 3.307004 | 0.947811 | 2.669385 |
| $A_6$ | 2.753463 | 1.696491 | 2.56005 | 1.77379 | 1.701056 | 3.074105 |
| $A_7$ | 3.156472 | 1.637114 | 1.373143 | 1.74784 | 0.865226 | 2.053645 |
| $A_8$ | 1.693049 | 1.960944 | 3.104344 | 1.389723 | 0.947811 | 0.588523 |

Table 8. The weighted expert decision matrix.

| | $SFC_{3111}$ | $SFC_{3121}$ | $SFC_{3211}$ | $SFC_{3221}$ | $SFC_{3311}$ | $SFC_{3321}$ |
|---|---|---|---|---|---|---|
| $A_1$ | 0.388076 | 0.347184 | 0.037729 | 0.010234 | 0.70779 | 0.071505 |
| $A_2$ | 0.389875 | 0.505088 | 0.088383 | 0.19529 | 0.029187 | 0.115524 |
| $A_3$ | 0.012333 | 0.728314 | 0.093972 | 0.102762 | 0.437444 | 0.103499 |
| $A_4$ | 0.442547 | 0.012344 | 0.159997 | 0.354081 | 0.207594 | 0.276657 |
| $A_5$ | 0.180883 | 0.538726 | 0.149238 | 0.461874 | 0.197634 | 0.324327 |
| $A_6$ | 0.485558 | 0.349755 | 0.378404 | 0.247737 | 0.354698 | 0.3735 |
| $A_7$ | 0.556626 | 0.337514 | 0.202966 | 0.244113 | 0.180414 | 0.249515 |
| $A_8$ | 0.29856 | 0.404276 | 0.458857 | 0.194096 | 0.197634 | 0.071505 |

Apply the steps of the weighted product method (WPM) to rank the alternatives.

We compute the weighted decision matrix using Eq. (8) as shown in Table 9.

Then we rank the alternatives. The alternatives are ranked based on product each row in the weighted decision matrix.

Table 9 The weighted decision matrix.

| | $SFC_{3111}$ | $SFC_{3121}$ | $SFC_{3211}$ | $SFC_{3221}$ | $SFC_{3311}$ | $SFC_{3321}$ |
|---|---|---|---|---|---|---|
| $A_1$ | 0.044005 | 0.051738 | 0.004869 | 0.00116 | 0.140938 | 0.005383 |
| $A_2$ | 0.044209 | 0.075269 | 0.011406 | 0.022145 | 0.005812 | 0.008697 |
| $A_3$ | 0.001398 | 0.108535 | 0.012128 | 0.011653 | 0.087106 | 0.007792 |
| $A_4$ | 0.050182 | 0.00184 | 0.020649 | 0.040151 | 0.041337 | 0.020827 |
| $A_5$ | 0.020511 | 0.080282 | 0.01926 | 0.052374 | 0.039354 | 0.024416 |
| $A_6$ | 0.055059 | 0.052121 | 0.048835 | 0.028092 | 0.070629 | 0.028118 |
| $A_7$ | 0.063118 | 0.050297 | 0.026194 | 0.027681 | 0.035925 | 0.018784 |
| $A_8$ | 0.033855 | 0.060246 | 0.059218 | 0.022009 | 0.039354 | 0.005383 |

In the fourth TreeSoft Set.

We created the decision matrix based on the opinions of three experts. Then we combine the different decision matrix into a single matrix.

Then we compute the normalized decision matrix using Eq. (2) as shown in Table 10.

Then we compute the weighted decision matrix using Eq. (3) as shown in table 11.

Then we obtain the max and min values of the weighted decision matrix using Eqs. (4 and 5).

Then we obtain the distance between the $s_{ij}^{max}$ and $s_{ij}^{min}$ using Eq. (6).

Then we calculate the criteria weights using Eq. (7).

Table 10. The normalized decision matrix.

| | $SFC_{4111}$ | $SFC_{4121}$ | $SFC_{4211}$ | $SFC_{4221}$ | $SFC_{4311}$ | $SFC_{4321}$ |
|---|---|---|---|---|---|---|
| $A_1$ | 1.909454 | 1.354729 | 0.225505 | 0.084976 | 3.252604 | 2.459429 |
| $A_2$ | 0.696155 | 3.287477 | 1.658923 | 2.782958 | 0.684053 | 2.889642 |
| $A_3$ | 1.278652 | 1.166071 | 1.213133 | 2.813054 | 1.332059 | 1.907363 |
| $A_4$ | 0.204584 | 1.149011 | 1.195385 | 1.66411 | 0.788002 | 2.969219 |
| $A_5$ | 0.045463 | 0.596081 | 0.620139 | 1.72076 | 0.814828 | 0.828099 |
| $A_6$ | 1.278652 | 0.104364 | 0.108576 | 0.283253 | 0.134128 | 1.768103 |
| $A_7$ | 1.789924 | 0.160561 | 0.528266 | 1.246312 | 0.087183 | 0.967359 |
| $A_8$ | 3.102862 | 0.975405 | 3.18839 | 1.611708 | 0.763188 | 0.258625 |

Table 11. The weighted expert decision matrix.

| | $SFC_{4111}$ | $SFC_{4121}$ | $SFC_{4211}$ | $SFC_{4221}$ | $SFC_{4311}$ | $SFC_{4321}$ |
|---|---|---|---|---|---|---|
| $A_1$ | 0.416114 | 0.237765 | 0.037803 | 0.011735 | 0.610489 | 0.278258 |
| $A_2$ | 0.151708 | 0.576976 | 0.278095 | 0.384333 | 0.128391 | 0.326932 |
| $A_3$ | 0.278647 | 0.204654 | 0.203365 | 0.38849 | 0.250017 | 0.215798 |
| $A_4$ | 0.044584 | 0.20166 | 0.20039 | 0.229818 | 0.147902 | 0.335935 |
| $A_5$ | 0.009907 | 0.104616 | 0.103958 | 0.237641 | 0.152937 | 0.093691 |
| $A_6$ | 0.278647 | 0.018317 | 0.018201 | 0.039118 | 0.025175 | 0.200042 |
| $A_7$ | 0.390065 | 0.02818 | 0.088556 | 0.172119 | 0.016364 | 0.109446 |
| $A_8$ | 0.676185 | 0.171191 | 0.534489 | 0.222581 | 0.143245 | 0.029261 |

Apply the steps of the weighted product method (WPM) to rank the alternatives.

We compute the weighted decision matrix using Eq. (8) as shown in Table 12.

Then we rank the alternatives. The alternatives are ranked based on product each row in the weighted decision matrix.

Table 12 The weighted decision matrix.

| | $SFC_{4111}$ | $SFC_{4121}$ | $SFC_{4211}$ | $SFC_{4221}$ | $SFC_{4311}$ | $SFC_{4321}$ |
|---|---|---|---|---|---|---|
| $A_1$ | 0.074159 | 0.041639 | 0.006157 | 0.000998 | 0.12727 | 0.016745 |

| | | | | | | |
|---|---|---|---|---|---|---|
| $A_2$ | 0.027037 | 0.101043 | 0.045293 | 0.032699 | 0.026766 | 0.019674 |
| $A_3$ | 0.04966 | 0.03584 | 0.033122 | 0.033052 | 0.052122 | 0.012986 |
| $A_4$ | 0.007946 | 0.035316 | 0.032637 | 0.019553 | 0.030834 | 0.020216 |
| $A_5$ | 0.001766 | 0.018321 | 0.016932 | 0.020218 | 0.031883 | 0.005638 |
| $A_6$ | 0.04966 | 0.003208 | 0.002964 | 0.003328 | 0.005248 | 0.012038 |
| $A_7$ | 0.069517 | 0.004935 | 0.014423 | 0.014644 | 0.003411 | 0.006586 |
| $A_8$ | 0.120508 | 0.02998 | 0.087052 | 0.018937 | 0.029863 | 0.001761 |

In fifth TreeSoft Set.

We created the decision matrix based on the opinions of three experts. Then we combine the different decision matrix into a single matrix.

Then we compute the normalized decision matrix using Eq. (2) as shown in Table 13.

Then we compute the weighted decision matrix using Eq. (3) as shown in table 14.

Then we obtain the max and min values of the weighted decision matrix using Eqs. (4 and 5).

Then we obtain the distance between the $s_{ij}^{max}$ and $s_{ij}^{min}$ using Eq. (6).

Then we calculate the criteria weights using Eq. (7).

Table 13. The normalized decision matrix.

| | $SFC_{5111}$ | $SFC_{5121}$ | $SFC_{5211}$ | $SFC_{5221}$ | $SFC_{5311}$ | $SFC_{5321}$ |
|---|---|---|---|---|---|---|
| $A_1$ | 1.089072 | 0.71888 | 0.372573 | 0.024709 | 1.69065 | 0.374747 |
| $A_2$ | 2.84669 | 1.508051 | 1.519143 | 0.694943 | 2.575375 | 1.383681 |
| $A_3$ | 2.988713 | 3.086392 | 1.539214 | 2.220728 | 3.460101 | 2.831856 |
| $A_4$ | 0.38935 | 2.188058 | 1.647724 | 2.983621 | 1.445888 | 2.007608 |
| $A_5$ | 2.68804 | 1.289724 | 3.635405 | 1.246779 | 2.452994 | 1.18336 |
| $A_6$ | 0.935272 | 2.495526 | 1.410633 | 2.1152 | 1.687307 | 2.007608 |
| $A_7$ | 1.309242 | 0.316307 | 1.375508 | 1.572115 | 0.580265 | 0.190061 |
| $A_8$ | 2.269593 | 0.517594 | 2.8451 | 0.468649 | 0.543491 | 0.050813 |

Table 14. The weighted expert decision matrix.

| | $SFC_{5111}$ | $SFC_{5121}$ | $SFC_{5211}$ | $SFC_{5221}$ | $SFC_{5311}$ | $SFC_{5321}$ |
|---|---|---|---|---|---|---|
| $A_1$ | 0.171188 | 0.122753 | 0.063925 | 0.004079 | 0.306703 | 0.057711 |
| $A_2$ | 0.447463 | 0.257508 | 0.260651 | 0.114713 | 0.467201 | 0.213087 |
| $A_3$ | 0.469787 | 0.527018 | 0.264094 | 0.366573 | 0.6277 | 0.436107 |
| $A_4$ | 0.061201 | 0.373622 | 0.282712 | 0.492503 | 0.2623 | 0.309172 |
| $A_5$ | 0.422525 | 0.220227 | 0.623754 | 0.205804 | 0.445 | 0.182238 |
| $A_6$ | 0.147013 | 0.426124 | 0.242033 | 0.349153 | 0.306096 | 0.309172 |

| | | | | | | |
|---|---|---|---|---|---|---|
| $A_7$ | 0.205796 | 0.054011 | 0.236006 | 0.259507 | 0.105267 | 0.029269 |
| $A_8$ | 0.356751 | 0.088382 | 0.488155 | 0.077359 | 0.098595 | 0.007825 |

Apply the steps of the weighted product method (WPM) to rank the alternatives.

We compute the weighted decision matrix using Eq. (8) as shown in Table 15.

Then we rank the alternatives. The alternatives are ranked based on product each row in the weighted decision matrix.

Table 15 The weighted decision matrix.

| | $SFC_{5111}$ | $SFC_{5121}$ | $SFC_{5211}$ | $SFC_{5221}$ | $SFC_{5311}$ | $SFC_{5321}$ |
|---|---|---|---|---|---|---|
| $A_1$ | 0.037077 | 0.036861 | 0.019196 | 0.001353 | 0.086497 | 0.018962 |
| $A_2$ | 0.096914 | 0.077326 | 0.07827 | 0.038063 | 0.131762 | 0.070015 |
| $A_3$ | 0.101749 | 0.158257 | 0.079304 | 0.121631 | 0.177026 | 0.143293 |
| $A_4$ | 0.013255 | 0.112194 | 0.084895 | 0.163415 | 0.073975 | 0.101586 |
| $A_5$ | 0.091513 | 0.066131 | 0.187305 | 0.068287 | 0.1255 | 0.059878 |
| $A_6$ | 0.031841 | 0.12796 | 0.072679 | 0.115851 | 0.086326 | 0.101586 |
| $A_7$ | 0.044572 | 0.016219 | 0.07087 | 0.086106 | 0.029688 | 0.009617 |
| $A_8$ | 0.077267 | 0.02654 | 0.146587 | 0.025668 | 0.027806 | 0.002571 |

Then we obtain the criteria weights and ranks of the alternatives of five TreeSoft sets as shown in Table 16 and 17.

Table 16. The criteria weights.

| | First TreeSoft Set | Second TreeSoft Set | Third TreeSoft Set | Fourth TreeSoft Set | Fifth TreeSoft Set |
|---|---|---|---|---|---|
| $C_1$ | 0.220382 | 0.263932 | 0.17481 | 0.220711 | 0.141515 |
| $C_2$ | 0.213916 | 0.122938 | 0.229947 | 0.185061 | 0.163827 |
| $C_3$ | 0.12757 | 0.156208 | 0.135253 | 0.171025 | 0.193898 |
| $C_4$ | 0.151104 | 0.136597 | 0.145053 | 0.124804 | 0.169167 |
| $C_5$ | 0.23682 | 0.24444 | 0.217946 | 0.19681 | 0.183257 |
| $C_6$ | 0.05021 | 0.075885 | 0.096991 | 0.101589 | 0.148336 |

Table 17. Final ranks of alternatives.

| | First TreeSoft Set | Second TreeSoft Set | Third TreeSoft Set | Fourth TreeSoft Set | Fifth TreeSoft Set |
|---|---|---|---|---|---|
| $A_1$ | 3 | 5 | 1 | 4 | 1 |
| $A_2$ | 6 | 4 | 3 | 8 | 5 |
| $A_3$ | 2 | 3 | 2 | 7 | 8 |

| | | | | | |
|---|---|---|---|---|---|
| **$A_4$** | 4 | 2 | 4 | 5 | 4 |
| **$A_5$** | 1 | 1 | 7 | 3 | 7 |
| **$A_6$** | 7 | 6 | 8 | 1 | 6 |
| **$A_7$** | 5 | 7 | 6 | 2 | 3 |
| **$A_8$** | 8 | 8 | 5 | 6 | 2 |

## 4. Conclusions

Student feedback is a vital component of teaching quality evaluation in international Chinese education. By leveraging student insights, institutions can create more effective, inclusive, and engaging learning environments. However, to maximize the benefits of feedback, educational systems must implement fair, transparent, and technology-driven methods for data collection and analysis. Addressing challenges such as response bias and inconsistent participation will further enhance the reliability of feedback mechanisms. As the field of international Chinese education continues to grow, student feedback will remain a cornerstone for continuous improvement, ensuring that teaching strategies align with evolving educational needs and global standards. We used two MCDM methods such as CIMAS method to compute the criteria weights and the WPM method to rank the alternatives. The Forest HyperSoft Set is used in this study to divide the main criteria into TreeSoft Sets. We had five TreeSoft Sets, in each it, we computed the criteria weights and ranked the alternatives.

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