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Developing a lecturer ranking system based on student evaluations

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Abstract

The quality of teaching is a critical component in enhancing student development within higher education. While student feedback is increasingly recognized as a valuable tool for assessing instructional effectiveness, existing evaluation systems often lack methodological diversity and fail to capture comprehensive performance insights. This study addresses the gap by proposing a multi-method faculty ranking system based on student evaluations, with a focus on a specific academic course. The objective is to develop a more nuanced and reliable mechanism for assessing teaching quality. Four distinct evaluation techniques were employed to rank faculty members: the Preference Selection Index (PSI) method, the Simple Ranking Process (SRP) method, the Ranking Analysis Method (RAM), and the Preference Index Value (PIV) method. These methods were systematically compared with each other and with conventional institutional practices. The analysis demonstrates that the proposed framework offers enhanced precision and consistency in ranking instructional performance. The findings highlight the potential for integrating multiple evaluative approaches to inform faculty development and support evidence-based decisions in academic management.

Keyword: Evaluation; lecturer; multi-criteria decision-making; ranking; student

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1. INTRODUCTION

Assessing and ranking faculty members, particularly in situations where several instructors are responsible for teaching the same course, plays a pivotal role in upholding educational standards and advancing faculty development (Shaath & Abed, 2024; Sabharwal & Miah, 2024; Ventista & Brown, 2023; Ekinci et al., 2022). Since each instructor brings a distinct pedagogical approach and perspective, evaluating their effectiveness provides valuable insights for both educational institutions and learners. This evaluation process assists in determining the most effective teaching methods and supports strategic decisions related to instructional assignments. Furthermore, it serves as a mechanism to recognize teaching excellence while simultaneously identifying areas that may require improvement (Munna & Kalam, 2021).

Faculty members who receive high student ratings can be encouraged to share their strategies with peers or be allocated more teaching responsibilities, thereby amplifying their positive influence. Conversely, instructors who score poorly may benefit from additional professional development, mentoring, or even a reassessment of their suitability for teaching a particular course. Effective faculty ranking also supports institutions in strategically managing their teaching personnel (Girvan et al., 2016). For instance, if a lecturer consistently underperforms, administrative decisions, such as limiting or ceasing their instructional assignments, can be made to uphold the institution's academic quality. This process contributes not only to better teaching outcomes but also to higher levels of motivation and professionalism within the academic workforce (Oliver et al., 2007). In essence, faculty ranking serves not just as a performance evaluation tool, but as a comprehensive strategy for managing human resources and enhancing the diversity and effectiveness of teaching practices.

When evaluations rely solely on administrators' subjective views or are narrowly based on a limited set of indicators, like research output or project involvement, they often fail to capture the full scope and complexity of an instructor's contributions. In Vietnam, several universities have recently begun incorporating student evaluations into faculty assessments, a practice that marks a shift from traditional methods. In this system, students must complete evaluations of their instructors before gaining access to their course grades. This requirement integrates evaluation directly into the academic process. The system collects student feedback on a set of predefined criteria, then calculates average scores for each criterion and produces an overall rating for each instructor.

However, using simple averages assumes that all evaluation criteria carry equal importance, which is not always appropriate. The relevance of a specific criterion often varies depending on the course's nature. For example, in a practical or hands-on course, an instructor's operational proficiency is essential, whereas in theory-heavy subjects, academic depth takes precedence. To account for such nuances and provide a more balanced and objective assessment, it is necessary to employ Multi-Criteria Decision-Making (MCDM) methods (Mondal & Pramanik, 2014; Malik et al., 2021; Ghorui et al., 2021). These approaches consider the relative importance of various criteria, making them more suitable for evaluating faculty performance across diverse academic settings.

MCDM techniques are designed to rank and select from a set of alternatives by considering multiple, often conflicting criteria. With over 200 methods developed to date, MCDM has been successfully implemented across various industries, including logistics, manufacturing, healthcare, and construction (Trung et al., 2022). In education, its utility has also been well-documented. For example, the PROMETHEE method has been used to rank participants in teaching competitions (Monalisa & Kusnawi, 2017), while the AHP and ARAS methods have evaluated lecturers based on factors like academic qualifications and years of service (Akmaludin et al., 2023). RAPS has been utilized to rank university departments based on metrics such as the number of professors, Scopus-indexed publications, and research productivity (Bafail et al., 2022). During the Covid-19 pandemic, the TOPSIS method helped select suitable online teaching platforms (Toan et al., 2021) and assess student academic performance (Sirigiri et al., 2015). Additionally, the VIKOR method has been applied to university rankings based on student perceptions (Ayyildiz et al., 2023).

1.1. Purpose of study

In this study, four specific MCDM methods, Preference Selection Index (PSI), Simple Ranking Process (SRP), Ranking Analysis Method (RAM), and Preference Index Value (PIV), are applied to evaluate instructors based on student feedback. These methods were chosen for their distinct features, allowing a comprehensive and balanced analysis. The PSI method involves data normalization but does not require assigning weights to criteria, making it relatively straightforward (Maniya & Bhatt, 2010; Do & Nguyen, 2023). In contrast, the SRP method requires weighting the criteria but does not involve data normalization, making it suitable when the number of alternatives exceeds five (Zakeri et al., 2023; Zakeri et al., 2024). RAM, a newly developed approach introduced in 2023, stands out for its ability to balance beneficial and non-beneficial criteria (Sotoudeh-Anvari, 2023). Meanwhile, PIV is particularly valued for reducing the likelihood of rank reversal, enhancing the consistency of results (Mufazzal & Muzakkir, 2018). Both RAM and PIV necessitate both data normalization and weighting. The integration of these four MCDM methods, each with its strengths, aims to ensure a more objective, reliable, and nuanced assessment of faculty teaching performance.

2. METHOD AND MATERIALS

2.1. PSI Method

The application of the PSI method to rank alternatives follows an eight-step sequence as follows (Maniya & Bhatt 2010; Do & Nguyen 2023).

Step 1: Construct the decision matrix with *m* rows and *m* columns, where *m* represents the number of alternatives to be ranked, and *m* denotes the number of criteria for each alternative. Let x_{ij} denote the value of criterion *j* for alternative *i*, where $j = 1 \div n$, $i = 1 \div m$. The letters B and C are used to signify profit criteria and cost criteria.

Step 2: Normalize the Data

Normalize the data using the following formulas (1) and (2)

$$n_{ij} = \frac{x_{ij}}{x_j^{max}} \; if \; j \epsilon B \tag{1}$$

$$n_{ij} = \frac{x_j^{min}}{x_{ij}} \; if \; j \epsilon C \tag{2}$$

Step 3: Calculate the Average Value of Normalized Data using the following formulas (3)

$$n = \frac{1}{m} \sum_{i=1}^{m} \quad n_{ij} \tag{3}$$

Step 4: Determine Preference Values from Average Normalized Values

Calculate the preference values based on the average normalized values using the following formula (4).

$$\varphi_j = \sum_{i=1}^{m} \quad \left[n_{ij} - n\right]^2 \tag{4}$$

Step 5: Determine deviation in preference values

To determine the deviation in preference values, use the following formula (5)

$$\emptyset_j = 1 - \varphi_j \tag{5}$$

Step 6: Determine the overall priority value for the criteria according to formula (6).

$$_j = \frac{\emptyset_j}{\sum_{j=1}^{n} \quad \emptyset_j} \tag{6}$$

Step 7: Calculate the priority selection index for each alternative

$$\theta_i = \sum_{j=1}^{n} \quad n_{ij} \cdot \quad _j \tag{7}$$

Step 8: Rank the alternatives according to the principle that the best alternative is the one with the highest $(_i$.

2.2. SRP Method

To rank alternatives using the SRP method, you need to follow four simple sequential steps (Zakeri et al., 2023; 2024).

Step 1: Similar to Step 1 of the PSI method

Step 2: Rank internal alternatives for each criterion. For criterion *j*, the rank of alternative *i* is denoted as r_{ij}. Note that internal ranking of alternatives uses only natural numbers, i.e, $r_{ij} \in N$. This can be illustrated summarily through a simple example. Suppose there are five alternatives to rank: A1, A2, A3, A4, and A5. There are three criteria to describe each alternative: C1, C2, and C3. Among them, C1 and C2 are of type B, while C3 is of type C. The illustrative data for this example is presented in Table 1.

Table 1

Illustrative data for Step 2 of the SRP method

	C1	C2	C3
A1	7	3	8
A2	5	6	2
A3	7.5	4	4
A4	5.4	6	2
A5	4.2	3	2

The internal ranking of alternatives is carried out as follows:

- For C1 (type B criterion): Since the values of this criterion differ across all five alternatives, the ranking of alternatives is based on the decreasing order of the criterion values among the alternatives $r_{31} = 1$, $r_{11} = 2$, $r_{41} = 3$, $r_{21} = 4$ và $r_{51} = 5$.

- For criterion C2 (type B criterion): Since the criterion values at A2 and A4 are both equal to 6, $r_{22} = r_{42} = 1$, next $r_{32} = 2$. Since the criterion value for A1 and A5 are also equal, so $r_{12} = r_{52} = 3$.

- For criterion C3 (type C criterion): Because the criterion values are the same for alternatives A2, A4, and A5 $r_{23} = r_{43} = r_{53} = 1$, next $r_{33} = 2$ and $r_{13} = 3$.

Step 3: Calculate the score for each alternative using formula (8). Where w_j is the weight of criterion *j*.

$$S_i = \sum_{j=1}^{n} \quad r_{ij} \cdot w_j \tag{8}$$

Step 4: Rank the alternatives in ascending order based on their score values.

2.3. RAM Method

The ranking of alternatives using the RAM method is conducted through the following six-step process (Sotoudeh-Anvari, 2023).

Step 1: Similar to Step 1 of the PSI method

Step 2: Normalize the data according to formula (9).

$$r_{ij} = \frac{x_{ij}}{\sum_{i=1}^{m} x_{ij}} \tag{9}$$

Step 3: Calculate the normalized values considering the weights of the criteria according to (10).

$$y_{ij} = w_j \cdot r_{ij} \tag{10}$$

Step 4: Calculate the weighted sum of normalized scores according to (11) and (12).

$$S_{+i} = \sum_{j=1}^{n} y_{+ij} \quad if \quad j \in B \tag{11}$$

$$S_{-i} = \sum_{j=1}^{n} y_{-ij} \quad if \quad j \in C \tag{12}$$

Step 5: Calculate the score for each alternative using formula (13).

$$RI_i = \sqrt[2+S_{-i}]{2 + S_{+i}} \tag{13}$$

Step 6: Rank the alternatives in descending order based on their score values.

2.4. PIV Method

The PIV method uses a six-step process to rank the options (Mufazzal & Muzakkir 2018).

Step 1: Similar to Step 1 of the PSI method

Step 2: Normalize the data according to formula (14).

$$n_{ij} = \frac{x_{ij}}{\sqrt{\sum_{i=1}^{m} x_{ij}^2}} \tag{14}$$

Step 3: Calculate the normalized values considering the weights of the criteria according to (15).

$$V_{ij} = w_j \times n_{ij} \tag{15}$$

Step 4: Evaluate the proximity weight index using the formula (16) and (17).

$$u_i = v_{max} - v_i \quad if \quad j \in B \tag{16}$$

$$u_i = v_i - v_{min} \quad if \quad j \in C \tag{17}$$

Step 5: Determine the overall neighborhood value range according to formula (18).

$$d_i = \sum_{j=1}^{n} u_i \tag{18}$$

Step 6: Rank the alternatives based on the principle that the best alternative is the one with d_i smallest distance.

3. RESULTS

3.1. Ranking faculty using MCDM methods

The course selected for this investigation is "Mechanical Engineering Design Project." It was chosen because it offers a balanced structure that includes both formal instruction in the classroom and opportunities for independent learning outside of class. This dual format allows students to absorb foundational concepts directly from their instructors while also giving them the space to explore topics further, apply their knowledge, and experiment with ideas through self-directed study. The course is particularly engaging for learners because it emphasizes the practical application of theoretical content, encouraging students to think creatively and solve real-world problems.

A key feature of this course is the instructor's role in guiding students through their project work. This mentorship is essential in helping learners develop a deeper understanding of the design process in mechanical engineering and to improve their ability to collaborate effectively within teams. Another strength of the course is the ability of students to ask questions and seek explanations through digital platforms or learning applications. This accessibility allows for quick clarification of doubts and supports active problem resolution. As a result, the learning experience remains dynamic and prevents students from becoming disengaged or overly reliant on passive methods of learning.

In order to access their exam results for a given course within the institution's academic management system, students are required to complete an evaluation of the instructor who delivered the course. This assessment is based on a set of seventeen specific criteria that have been established by school administrators. For each of these criteria, students assign a score between zero and five, where higher values reflect stronger performance in that area. Each of the seventeen criteria is categorized under group B, meaning they are considered essential aspects for evaluating teaching effectiveness.

3.1.1. C1: The instructor always prepares well for classes.

This criterion emphasizes the critical role that thorough planning and organization play in the educational process. When educators dedicate sufficient time to preparing for their lessons, they are better equipped to design effective and engaging learning experiences that promote student comprehension and participation. Solid preparation allows teachers to adapt more easily to unforeseen circumstances during instruction and improves the clarity and effectiveness of their communication. From the student's perspective, well-prepared lessons are reflected in structured, coherent, and precise delivery, which significantly contributes to developing a sense of confidence in and appreciation for the instructor's capabilities.

3.1.2. C2: Lessons are structured and organized systematically

The value of carefully organizing and structuring lessons is rooted in its ability to support students in grasping and retaining information in a clear and logical way. When instructors present material in a well-ordered sequence, it becomes easier for learners to follow along, categorize knowledge, and make sense of complex topics. A logical arrangement of content not only strengthens the connection between different parts of the lesson but also deepens students' comprehension and encourages the integration of ideas, thereby reinforcing their academic foundation. Furthermore, a clearly structured lesson allows students to anticipate upcoming topics, which can enhance their sense of security and self-assurance in the learning environment. This clarity promotes sustained focus and contributes to a more productive and effective educational experience.

3.1.3. C3: The instructor teaches with passion

A deep enthusiasm for teaching serves as a powerful driving force and significantly contributes to shaping a supportive and engaging learning atmosphere. When educators express their subject matter with genuine enthusiasm, it often inspires students and sparks their creativity. This passion becomes contagious, awakening curiosity and a desire to learn more deeply within the classroom. Moreover, a passionate instructor is more likely to persevere through teaching difficulties, adapting and maintaining energy even in the face of obstacles. Such dedication does more than just transfer knowledge; it nurtures a constructive and stimulating environment that supports the intellectual and personal growth of students in a well-rounded manner (as reflected in related literature and findings).

3.1.4. C4: The instructor motivates students in learning this course

This emphasizes the critical role that instructors play in fostering motivation among students. When educators are able to spark curiosity and stimulate interest in the subject matter, they contribute significantly to building a constructive and engaging learning environment. Such motivation not only boosts student enthusiasm but also encourages greater self-management and a stronger sense of responsibility in their academic pursuits. The drive to learn can emerge from various sources, such as the opportunity to tackle practical problems, apply theoretical knowledge to real-life situations, or realize how the course content aligns with their personal development and professional aspirations (as supported by existing research and educational insights).

3.1.5. C5: Students receive timely support with course syllabus and official materials

Ensuring that students receive adequate support in obtaining course syllabi and authorized learning materials is essential for fostering effective learning. When students are promptly provided with the necessary documents and guidance, they are better equipped to navigate academic challenges and deepen their comprehension of the subject matter. This support enhances their capacity to engage with and apply the content meaningfully. Moreover, distributing standardized and official materials guarantees that all learners have access to consistent and reliable information, which contributes to a more coherent educational experience and simplifies the process of studying and revisiting course topics (as emphasized by relevant educational frameworks and literature).

3.1.6. C6: Course materials are easy to access and regularly updated

The accessibility and consistent updating of course content are vital elements that significantly enhance students' ability to manage their study time effectively. When educational materials are clearly organized and easy to navigate, learners can swiftly locate and utilize the necessary information, which improves their productivity in reviewing and understanding course concepts. In addition, regularly refreshing the course content ensures that students are exposed to current developments and innovations within the discipline. This approach not only supports the continuity of learning but also equips students to apply their knowledge in practical, real-world contexts, thereby reinforcing their academic and professional preparedness (as highlighted in contemporary educational research and practice).

3.1.7. C7: The instructor provides clear and comprehensive communication of the course overview and distribution of time before teaching

Providing students with clear and detailed communication before instructional sessions emphasizes the critical role of preparation and openness in the teaching process. When students receive advance notice regarding the content, objectives, and schedule of a course, they are better positioned to organize their learning activities and allocate their time efficiently. Such proactive communication enhances students' readiness and promotes a sense of direction in their academic pursuits. Moreover, this level of transparency nurtures a cooperative and inclusive learning atmosphere, encouraging mutual engagement between instructors and learners. It helps build a sense of shared responsibility, enabling both parties to contribute meaningfully to the success of the educational experience (as supported by existing literature and pedagogical best practices).

3.1.8. C8: The instructor communicates clear and comprehensive course learning outcomes before teaching

The learning outcomes of a course are essential benchmarks for the knowledge and competencies that students are expected to acquire by the end of the course. Clearly outlining these outcomes enables students to grasp the course's goals and design an effective learning strategy. Moreover, transparent communication of these outcomes allows instructors to align their expectations with those of the students, facilitating a more accurate and equitable assessment of students' achievements. This clarity ensures that evaluations are consistent and aligned with the intended learning objectives, promoting fairness and transparency in the overall assessment process.

3.1.9. C9: The instructor arrives on time for classes, ensuring the schedule and teaching workload align with the course syllabus.

Maintaining punctuality and adhering to the prescribed teaching workload is essential for cultivating a structured learning environment and assisting students in effectively managing their time. When instructors stick to the established schedule and follow the course outline, students can depend on this predictability to plan their studies and engage meaningfully in the lessons. Consistency and reliability in teaching contribute to the stability and overall quality of the educational experience, ensuring that students have a steady framework within which they can learn and succeed.

3.1.10. C10: The instructor guides students on study methods at the beginning of the course

At the start of a course, providing guidance on effective study techniques is essential for enabling students to create a tailored study plan that aligns with their individual learning preferences. This approach fosters greater independence in their learning process and lays the groundwork for cultivating self-learning abilities, which are vital for their broader academic growth and success.

3.1.11. C11: The instructor's teaching method is clear and effective

The clarity and effectiveness of the teaching approach are essential in shaping how well students comprehend and retain information. When instructors choose methods that align with the needs of their students, the delivery of content becomes more structured and engaging. This strategy not only facilitates a deeper understanding of the material but also improves students' ability to apply what they've learned in practical contexts, bridging the gap between theoretical knowledge and real-world scenarios.

3.1.12. C12: The instructor creates opportunities for students to actively participate in the learning process

It is vital for instructors to provide opportunities for students to engage actively in the learning process, as this promotes interaction and involvement. When students are encouraged to participate by discussing, asking questions, and sharing ideas, it not only deepens their comprehension but also cultivates their communication and critical thinking skills. Active involvement boosts students' confidence and enthusiasm for learning, while also contributing to a positive and motivating classroom atmosphere.

3.1.13. C13: Student learning outcomes are assessed through various forms of assessment that align with course learning outcomes.

The variety in evaluating student learning outcomes and its alignment with course objectives is essential for achieving fairness and precision in assessments. By incorporating different assessment types, such as exams, projects, presentations, and group discussions, instructors provide students with multiple ways to showcase their abilities and knowledge. This diverse evaluation approach not only enriches the learning experience but also supports the development of a wide range of skills and competencies in students.

3.1.14. C14: Feedback from assessments helps you improve your learning outcomes.

Feedback plays an essential role in the learning journey, offering students insight into their strengths and areas for improvement. When instructors deliver thorough and constructive feedback, it allows students to evaluate their own skills and performance, encouraging them to find ways to improve. Providing accurate and helpful feedback not only aids in immediate learning but also lays the groundwork for ongoing growth and lifelong education (Mendzheritskaya et al., 2025).

3.1.15. C15: The instructor's teaching method stimulates students' critical thinking and problem-solving abilities.

Encouraging students to develop critical thinking and problem-solving skills is vital for equipping them with the necessary tools for success in the real world (Wijnen et al., 2023). When instructors design lessons and activities that promote logical reasoning, data analysis, and problem resolution, students not only gain a deeper understanding of the course material but also build essential competencies that are valuable in their professional lives and everyday activities (Paz-Baruch et al., 2025).

3.1.16. C16: I learned a lot about the subject from the instructor.

This statement highlights the effectiveness of knowledge delivery and the creation of a constructive learning environment. When students recognize that they are gaining both knowledge and personal growth from their instructors, they are more likely to evaluate the learning experience positively and view the subject as a significant aspect of their academic development.

3.1.17. C17: Overall evaluation - The instructor is very suitable for teaching this course.

Overall assessment serves as the final and thorough measure of an instructor's effectiveness in delivering a course. By gathering data from the educational management system of the school regarding the scores across seventeen criteria for eight instructors teaching the "Machine Manufacturing Technology Project" course, the results presented in Table 2 are obtained.

Table 2

Aggregate students' feedback on each instructor

Lecturers	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	C12	C13	C14	C15	C16	C17
L1	4.67	4.7	4.7	4.7	4.7	4.73	4.67	4.7	4.73	4.73	4.67	4.67	4.7	4.7	4.7	4.67	4.67
L2	4.58	4.54	4.54	4.46	4.51	4.55	4.6	4.54	4.57	4.52	4.55	4.6	4.55	4.48	4.57	4.6	4.65
L3	4.66	4.63	4.68	4.63	4.76	4.71	4.68	4.74	4.76	4.68	4.74	4.74	4.74	4.74	4.76	4.76	4.76
L4	4.51	4.49	4.51	4.49	4.54	4.52	4.52	4.54	4.55	4.52	4.58	4.57	4.55	4.57	4.55	4.58	4.57
L5	4.82	4.77	4.88	4.85	4.86	4.92	5	4.85	5	5	5	5	5	5	5	4.98	4.97
L6	5	4.5	5	4.5	5	5	4.5	5	4.5	5	4.5	4.5	5	4.5	4.5	5	5
L7	4.76	4.68	4.76	4.68	4.72	4.76	4.8	4.72	4.8	4.76	4.76	4.8	4.72	4.64	4.76	4.72	4.76
L8	4.67	4.63	4.63	4.59	4.52	4.52	4.53	4.53	4.55	4.56	4.64	4.66	4.66	4.66	4.66	4.73	4.73

Currently, the university management relies on the data from the seventeen criteria in Table 2 to calculate the average scores of each instructor, which are then used to rank the instructors in Table 3. These results will be used to compare with the ranking of instructors using Multiple Criteria Decision Making (MCDM) methods as conducted in this study.

Table 3

Traditional ranking of instructors

Lecturers	Score	Rank
L1	4.69	5
L2	4.55	7
L3	4.72	4
L4	4.54	8
L5	4.94	1
L6	4.76	2
L7	4.74	3
L8	4.62	6

3.2. Applying the PSI method

The standardized values have been calculated using two formulas (1) and (2), resulting in the values shown in Table 4.

Table 4

The standardized values in PSI method

Lecturers	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	C12	C13	C14	C15	C16	C17
L1	0.9340	0.9853	0.9400	0.9691	0.9400	0.9460	0.9340	0.9400	0.9460	0.9460	0.9340	0.9340	0.9400	0.9400	0.9400	0.9340	0.9340
L2	0.9160	0.9518	0.9080	0.9196	0.9020	0.9100	0.9200	0.9080	0.9140	0.9040	0.9100	0.9200	0.9100	0.8960	0.9140	0.9200	0.9300
L3	0.9320	0.9706	0.9360	0.9546	0.9520	0.9420	0.9360	0.9480	0.9520	0.9360	0.9480	0.9480	0.9480	0.9480	0.9520	0.9520	0.9520
L4	0.9020	0.9413	0.9020	0.9258	0.9080	0.9040	0.9040	0.9080	0.9100	0.9040	0.9160	0.9140	0.9100	0.9140	0.9100	0.9160	0.9140
L5	0.9640	1.0000	0.9760	1.0000	0.9720	0.9840	1.0000	0.9700	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	0.9960	0.9940
L6	1.0000	0.9434	1.0000	0.9278	1.0000	1.0000	0.9000	1.0000	0.9000	1.0000	0.9000	0.9000	1.0000	0.9000	0.9000	1.0000	1.0000
L7	0.9520	0.9811	0.9520	0.9649	0.9440	0.9520	0.9600	0.9440	0.9600	0.9520	0.9520	0.9600	0.9440	0.9280	0.9520	0.9440	0.9520
L8	0.9340	0.9706	0.9260	0.9464	0.9040	0.9040	0.9060	0.9060	0.9100	0.9120	0.9280	0.9320	0.9320	0.9320	0.9320	0.9460	0.9460

Apply formula (3) to calculate the average values of normalized data (n); priority values from average values (φj) calculated by formula (4); deviation in priority values (Øj) calculated by formula (5); overall priority values for criteria calculated by formula (6). All calculated values have been compiled in Table 5.

Table 5

Data values of PSI

	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	C12	C13	C14	C15	C16	C17
n	0.9418	0.9680	0.9425	0.9510	0.9403	0.9428	0.9325	0.9405	0.9365	0.9443	0.9360	0.9385	0.9480	0.9323	0.9375	0.9510	0.9528
φj	0.0065	0.0031	0.0077	0.0051	0.0085	0.0092	0.0081	0.0078	0.0082	0.0106	0.0069	0.0068	0.0086	0.0076	0.0071	0.0070	0.0064
Øj	0.9935	0.9969	0.9923	0.9949	0.9915	0.9908	0.9919	0.9922	0.9918	0.9894	0.9931	0.9932	0.9914	0.9924	0.9929	0.9930	0.9936
βj	0.0589	0.0591	0.0588	0.0590	0.0588	0.0587	0.0588	0.0588	0.0588	0.0586	0.0588	0.0589	0.0587	0.0588	0.0588	0.0588	0.0589

The Preference selection index (*ϑi*) for each lecturer has been calculated using formula (7), as shown in Table 6. The ranking of each lecturer has also been arranged according to their ϑ_i values and placed in the last column of this table.

Table 6

Preference selection index (ϑi) the ranking of the lecturers

Lecturers	θi	Rank
L1	0.9433	5
L2	0.9149	7
L3	0.9475	4
L4	0.9120	8
L5	0.9915	1
L6	0.9571	2
L7	0.9526	3
L8	0.9275	6

3.3. Applying the SRP method

The internal ranking of the lecturers has been conducted according to step 2, with the results shown in Table 7.

Table 7

The internal ranking of the lecturers according to the SRP method.

Lecturers	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	C12	C13	C14	C15	C16	C17
L1	4	2	4	2	5	4	4	5	4	3	4	4	4	3	3	6	5
L2	6	5	7	8	8	6	5	6	5	6	7	6	6	8	5	7	6
L3	5	4	5	4	3	5	3	3	3	4	3	3	2	2	2	3	3
L4	7	7	8	7	6	7	7	6	6	6	6	7	6	6	6	8	7
L5	2	1	2	1	2	2	1	2	1	1	1	1	1	1	1	2	2
L6	1	6	1	6	1	1	8	1	7	1	8	8	1	7	7	1	1
L7	3	3	3	3	4	3	2	4	2	2	2	2	3	5	2	5	3
L8	4	4	6	5	7	7	6	7	6	5	5	5	5	4	4	4	4

The scores (Si) for each lecturer have been calculated using formula (8), where the weights of the criteria are equal, meaning each criterion has a weight of 1/17. The scores and rankings of the lecturers have been aggregated in Table 8.

Table 8

The scores and rankings of the lecturers

Lecturers	Si	Rank
L1	3.8824	5
L2	6.2941	7
L3	3.3529	3
L4	6.6471	8
L5	1.4118	1
L6	3.8824	4
L7	3.0000	2
L8	5.1765	6

3.4. Applying the RAM method

The normalized values have been calculated according to (9), with the results shown in Table 9.

Table 9

The normalized values in the RAM method

Lecturers	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	C12	C13	C14	C15	C16	C17
L1	0.1240	0.1272	0.1247	0.1274	0.1250	0.1254	0.1252	0.1249	0.1263	0.1252	0.1247	0.1244	0.1239	0.1260	0.1253	0.1228	0.1225
L2	0.1216	0.1229	0.1204	0.1209	0.1199	0.1207	0.1233	0.1207	0.1220	0.1197	0.1215	0.1225	0.1200	0.1201	0.1219	0.1209	0.1220
L3	0.1237	0.1253	0.1241	0.1255	0.1266	0.1249	0.1255	0.1260	0.1271	0.1239	0.1266	0.1263	0.1250	0.1271	0.1269	0.1251	0.1249
L4	0.1197	0.1215	0.1196	0.1217	0.1207	0.1199	0.1212	0.1207	0.1215	0.1197	0.1223	0.1217	0.1200	0.1226	0.1213	0.1204	0.1199
L5	0.1280	0.1291	0.1294	0.1314	0.1292	0.1305	0.1340	0.1289	0.1335	0.1324	0.1335	0.1332	0.1319	0.1341	0.1333	0.1309	0.1304
L6	0.1327	0.1218	0.1326	0.1220	0.1329	0.1326	0.1206	0.1329	0.1201	0.1324	0.1202	0.1199	0.1319	0.1207	0.1200	0.1314	0.1312
L7	0.1264	0.1267	0.1263	0.1268	0.1255	0.1262	0.1287	0.1255	0.1281	0.1260	0.1271	0.1279	0.1245	0.1244	0.1269	0.1241	0.1249
L8	0.1240	0.1253	0.1228	0.1244	0.1202	0.1199	0.1214	0.1204	0.1215	0.1207	0.1239	0.1241	0.1229	0.1250	0.1243	0.1243	0.1241

The normalized values considering the weights of the criteria have been calculated according to (10). Each criterion has been assigned an equal weight (1/17), with the results shown in Table 10.

Table 10

The normalized values taking into account the weights of the criteria (in the RAM method)

Lecturers	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	C12	C13	C14	C15	C16	C17
L1	0.0073	0.0075	0.0073	0.0075	0.0074	0.0074	0.0074	0.0073	0.0074	0.0074	0.0073	0.0073	0.0073	0.0074	0.0074	0.0072	0.0072
L2	0.0072	0.0072	0.0071	0.0071	0.0071	0.0071	0.0073	0.0071	0.0072	0.0070	0.0071	0.0072	0.0071	0.0071	0.0072	0.0071	0.0072
L3	0.0073	0.0074	0.0073	0.0074	0.0074	0.0073	0.0074	0.0074	0.0075	0.0073	0.0074	0.0074	0.0074	0.0075	0.0075	0.0074	0.0073
L4	0.0070	0.0071	0.0070	0.0072	0.0071	0.0071	0.0071	0.0071	0.0071	0.0070	0.0072	0.0072	0.0071	0.0072	0.0071	0.0071	0.0071
L5	0.0075	0.0076	0.0076	0.0077	0.0076	0.0077	0.0079	0.0076	0.0079	0.0078	0.0079	0.0078	0.0078	0.0079	0.0078	0.0077	0.0077
L6	0.0078	0.0072	0.0078	0.0072	0.0078	0.0078	0.0071	0.0078	0.0071	0.0078	0.0071	0.0071	0.0078	0.0071	0.0071	0.0077	0.0077
L7	0.0074	0.0075	0.0074	0.0075	0.0074	0.0074	0.0076	0.0074	0.0075	0.0074	0.0075	0.0075	0.0073	0.0073	0.0075	0.0073	0.0073
L8	0.0073	0.0074	0.0072	0.0073	0.0071	0.0071	0.0071	0.0071	0.0071	0.0071	0.0073	0.0073	0.0072	0.0074	0.0073	0.0073	0.0073

The total standardized score considering the weights of the criteria has been calculated according to (11) and (12); the scores of each lecturer have been calculated according to (13). Table 11 summarizes the calculated values and the rankings of the lecturers according to their scores (RI_i).

Table 11

Some parameters in the RAM method and the rankings of the lecturers

Lecturers	S_{+i}	S_{-i}	RI_i	Rank
L1	0.125002		1.4577	5
L2	0.121237		1.4564	7
L3	0.125559		1.4579	4
L4	0.120848	0	1.4563	8
L5	0.131401		1.4599	1
L6	0.126821		1.4584	2
L7	0.126235		1.4582	3
L8	0.122897		1.4570	6

3.5. Applying the RAM method

The standardized values calculated according to (14) are summarized in Table 12.

Table 12

The standardized values calculated according to (14) are summarized in Table 12.

Lecturers	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	C12	C13	C14	C15	C16	C17
L1	0.3505	0.3598	0.3524	0.3601	0.3532	0.3545	0.3539	0.3532	0.3569	0.3539	0.3526	0.3517	0.3504	0.3563	0.3543	0.3471	0.3464
L2	0.3437	0.3475	0.3404	0.3417	0.3390	0.3411	0.3486	0.3411	0.3449	0.3382	0.3436	0.3464	0.3392	0.3396	0.3445	0.3419	0.3450
L3	0.3497	0.3544	0.3509	0.3548	0.3578	0.3530	0.3547	0.3562	0.3592	0.3502	0.3579	0.3570	0.3533	0.3593	0.3588	0.3538	0.3531
L4	0.3385	0.3437	0.3382	0.3440	0.3412	0.3388	0.3425	0.3411	0.3433	0.3382	0.3458	0.3442	0.3392	0.3464	0.3430	0.3404	0.3390
L5	0.3617	0.3652	0.3659	0.3716	0.3653	0.3688	0.3789	0.3644	0.3773	0.3741	0.3775	0.3765	0.3727	0.3790	0.3769	0.3701	0.3687
L6	0.3753	0.3445	0.3749	0.3448	0.3758	0.3748	0.3410	0.3757	0.3396	0.3741	0.3398	0.3389	0.3727	0.3411	0.3392	0.3716	0.3709
L7	0.3572	0.3583	0.3569	0.3586	0.3547	0.3568	0.3638	0.3547	0.3622	0.3562	0.3594	0.3615	0.3519	0.3517	0.3588	0.3508	0.3531
L8	0.3505	0.3544	0.3472	0.3517	0.3397	0.3388	0.3433	0.3404	0.3433	0.3412	0.3504	0.3509	0.3474	0.3533	0.3513	0.3515	0.3509

The standardized values considering the weights of the criteria have been calculated according to (15), with the results shown in Table 13. Here, the weight of each criterion was also chosen to be 1/17.

Table 13

The standardized values considering the weights of the criteria (PIV method)

Lecturers	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	C12	C13	C14	C15	C16	C17
L1	0.0206	0.0212	0.0207	0.0212	0.0208	0.0209	0.0208	0.0208	0.0210	0.0208	0.0207	0.0207	0.0206	0.0210	0.0208	0.0204	0.0204
L2	0.0202	0.0204	0.0200	0.0201	0.0199	0.0201	0.0205	0.0201	0.0203	0.0199	0.0202	0.0204	0.0200	0.0200	0.0203	0.0201	0.0203
L3	0.0206	0.0208	0.0206	0.0209	0.0210	0.0208	0.0209	0.0210	0.0211	0.0206	0.0211	0.0210	0.0208	0.0211	0.0211	0.0208	0.0208
L4	0.0199	0.0202	0.0199	0.0202	0.0201	0.0199	0.0201	0.0201	0.0202	0.0199	0.0203	0.0202	0.0200	0.0204	0.0202	0.0200	0.0199
L5	0.0213	0.0215	0.0215	0.0219	0.0215	0.0217	0.0223	0.0214	0.0222	0.0220	0.0222	0.0221	0.0219	0.0223	0.0222	0.0218	0.0217
L6	0.0221	0.0203	0.0221	0.0203	0.0221	0.0220	0.0201	0.0221	0.0200	0.0220	0.0200	0.0199	0.0219	0.0201	0.0200	0.0219	0.0218
L7	0.0210	0.0211	0.0210	0.0211	0.0209	0.0210	0.0214	0.0209	0.0213	0.0210	0.0211	0.0213	0.0207	0.0207	0.0211	0.0206	0.0208
L8	0.0206	0.0208	0.0204	0.0207	0.0200	0.0199	0.0202	0.0200	0.0202	0.0201	0.0206	0.0206	0.0204	0.0208	0.0207	0.0207	0.0206

The weighted proximity index has been calculated according to (16) and (17), with the results shown in Table 14.

Table 14

The values of the weighted proximity index in the PIV method

Lecturers	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	C12	C13	C14	C15	C16	C17
L1	0.0015	0.0003	0.0013	0.0007	0.0013	0.0012	0.0015	0.0013	0.0012	0.0012	0.0015	0.0015	0.0013	0.0013	0.0013	0.0014	0.0014
L2	0.0019	0.0010	0.0020	0.0018	0.0022	0.0020	0.0018	0.0020	0.0019	0.0021	0.0020	0.0018	0.0020	0.0023	0.0019	0.0017	0.0015
L3	0.0015	0.0006	0.0014	0.0010	0.0011	0.0013	0.0014	0.0011	0.0011	0.0014	0.0012	0.0012	0.0011	0.0012	0.0011	0.0010	0.0010
L4	0.0022	0.0013	0.0022	0.0016	0.0020	0.0021	0.0021	0.0020	0.0020	0.0021	0.0019	0.0019	0.0020	0.0019	0.0020	0.0018	0.0019
L5	0.0008	0.0000	0.0005	0.0000	0.0006	0.0004	0.0000	0.0007	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0001	0.0001
L6	0.0000	0.0012	0.0000	0.0016	0.0000	0.0000	0.0022	0.0000	0.0022	0.0000	0.0022	0.0022	0.0000	0.0022	0.0022	0.0000	0.0000
L7	0.0011	0.0004	0.0011	0.0008	0.0012	0.0011	0.0009	0.0012	0.0009	0.0011	0.0011	0.0009	0.0012	0.0016	0.0011	0.0012	0.0010
L8	0.0015	0.0006	0.0016	0.0012	0.0021	0.0021	0.0021	0.0021	0.0020	0.0019	0.0016	0.0015	0.0015	0.0015	0.0015	0.0012	0.0012

The overall proximity value (d_i) of each lecturer has been calculated according to (18), with the results shown in Table 15. The ranking of each lecturer has also been determined according to their d_i value and is summarized in the last column of this table.

Table 15

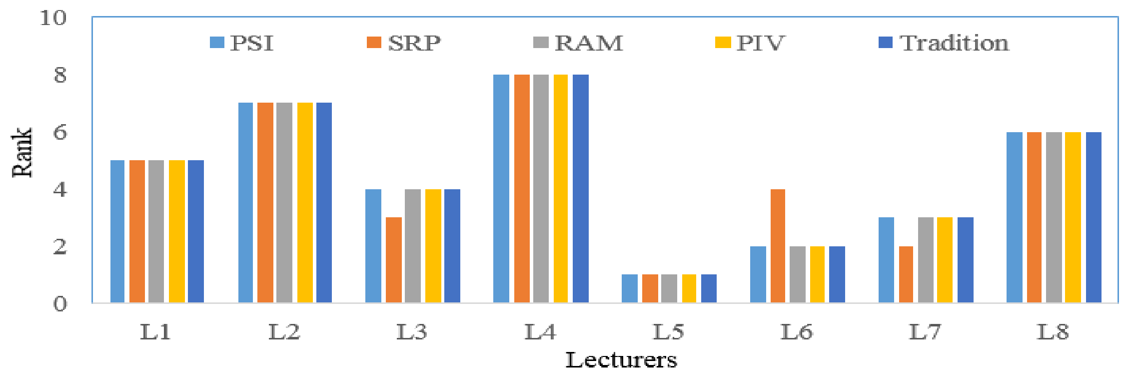
The d_i value and the ranking of each lecturer

Lecturers	di	rank
L1	0.0213	5
L2	0.0319	7
L3	0.0197	4
L4	0.0330	8
L5	0.0032	1
L6	0.0161	2
L7	0.0178	3
L8	0.0272	6

Thus, the ranking of lecturers using the four methods PSI, SRP, RAM, and PIV has been completed. The ranking results according to the traditional method currently used by the university have also been used to compare with the ranking results of the lecturers by these four methods. Figure 1 shows the ranking chart of lecturers using different methods.

Figure 1

Ranking of lecturers using different methods when the weights of the criteria are equal



It is evident that the rankings of the lecturers obtained using the PSI, RAM, and PIV methods are fully consistent with each other and align completely with the rankings derived from the traditional method currently employed at the university. However, there is a minor discrepancy in the rankings when using the SRP method, compared to the other methods. Despite this, the lecturer rated highest and the one rated lowest using the SRP method always correspond with those ranked similarly in the other methods. This difference in rankings can be attributed to the fact that the SRP method relies solely on natural numbers for internal ranking, which limits its adaptability compared to other methods that normalize the data into real numbers, including both natural and decimal values.

The findings and conclusions drawn are based on the assumption that all the selected criteria are weighted equally (each receiving a weight of 1/17). But do these results remain valid when the weights of the criteria are determined using other methods? To explore this, it is necessary to rank the lecturers again while incorporating varying criteria weights derived from different methods. Two weighting methods, Entropy and MEREC, have been highlighted for their high accuracy in assigning weights (Trung & Thinh, 2021), and they have been frequently used in recent research (Thinh, 2023; Trung, 2021a, 2021b; Le et al., 2022). These methods were chosen for this study because of their proven reliability. The calculated weights for each of the seventeen criteria for the lecturers, using the Entropy and MEREC methods, are displayed in Table 16.

Table 16

Weighting of the criteria

Weight method	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	C12	C13	C14	C15	C16	C17
Entropy	0.0588	0.0591	0.0588	0.0591	0.0588	0.0588	0.0589	0.0588	0.0589	0.0587	0.0589	0.0588	0.0587	0.0589	0.0588	0.0587	0.0586
MEREC	0.0648	0.0422	0.0657	0.0503	0.0619	0.0624	0.0527	0.0556	0.0593	0.0645	0.0587	0.0628	0.0608	0.0592	0.0611	0.0559	0.0622

The ranking of lecturers using the SRP, RAM, and PIV methods when the weights of the criteria are calculated using the two methods Entropy and MEREC has also been conducted similarly to when the weights of all criteria were equal, as previously carried out. Figures 2 and 3 respectively show the rankings of the lecturers when the weights of the criteria are calculated using the two methods Entropy and MEREC. It should also be noted that since the PSI method does not involve the weights of the criteria, the rankings of the lecturers using this method do not depend on the weights of the criteria.

Figure 2

Ranking of lecturers using different methods when the weights of the criteria are calculated using the Entropy method

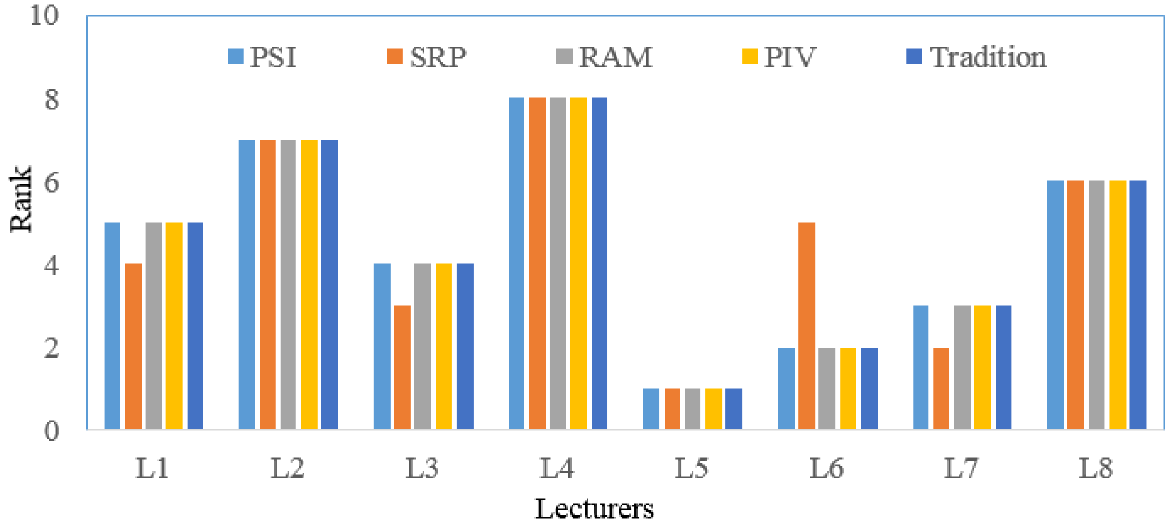
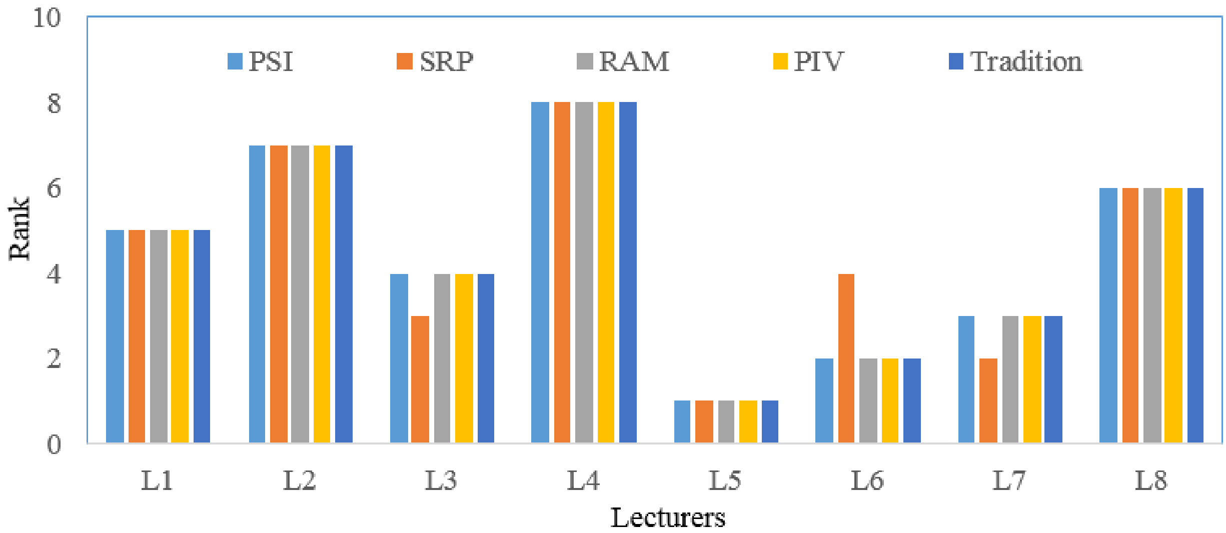


Figure 3

Ranking of lecturers using different methods when the weights of the criteria are calculated using the MEREC method.



In Figures 2 and 3, we also notice that the rankings of the lecturers are entirely consistent when ranked by the PSI, RAM, PIV methods, and the traditional method of the university. Furthermore, the ranking of each lecturer does not change when the weights of the criteria change (see Figures 1, 2, and 3). Additionally, the slight differences in the rankings of the lecturers when using the SRP method compared to the other methods remain, as observed in Figure 1 above. However, the lecturer ranked 1st and the lecturer ranked 8th remain consistent across different methods. All these observations suggest that applying the four methods PSI, SRP, RAM, and PIV is entirely appropriate for identifying the best lecturer for a course. The lecturer deemed least suitable for teaching a course can also be identified using these methods.

4. DISCUSSION

In the evaluation of instructors for the "Machine Manufacturing Technology Project" course, various methods are applied to rank the lecturers based on the feedback data collected from students. Traditional ranking using average scores (Table 3) is the first step, yielding the following hierarchy: L5, L6, L7, L3, L1, L8, L2, and L4. This basic ranking, however, relies solely on average scores without incorporating any weight for the significance of different criteria. While this method is straightforward, it may not fully reflect the complex nature of instructor effectiveness, as it treats all feedback criteria equally and fails to address the variability in individual instructor performance across different dimensions.

The introduction of advanced techniques such as the Preference Selection Index (PSI) method offers a more nuanced approach. The PSI method standardizes the data using specific formulas to account for discrepancies between instructors' performances across criteria (Table 4). By calculating the average normalized values and determining priority values (φj), the PSI method yields a more refined ranking, as demonstrated in Table 6, where the final ranking of lecturers adjusts according to more sophisticated calculations, with L5 ranked first. This method allows for better comparison by considering the normalized scores and prioritizing the most critical aspects of teaching based on the data provided, thereby offering a more comprehensive assessment of teaching effectiveness.

Furthermore, the use of the SRP and RAM methods further enhances the evaluation process by accounting for the relative importance of various criteria and normalizing the data accordingly. The SRP method calculates internal rankings for each lecturer (Table 7), whereas the RAM method normalizes data and applies weightings to derive more precise scores, resulting in a refined ranking of lecturers (Table 11). These methods help to further distinguish the subtle differences in teaching quality that may not be evident through traditional methods. Ultimately, the combination of these sophisticated evaluation tools provides a more detailed and objective ranking of the instructors, offering university management a clearer picture of instructor effectiveness beyond average scores.

5. CONCLUSION

The PSI, RAM, PIV methods, and the traditional ranking method all yield similar results in terms of lecturer rankings. This consistency highlights the reliability of these approaches in evaluating teaching performance within the machine technology project course.

Notably, the lecturer deemed most suitable, as well as the one identified as least suitable for teaching the course, consistently maintain their respective positions across all five evaluation methods, PSI, SRP, RAM, PIV, and the traditional ranking method. This further supports the robustness of the evaluation framework.

There is also strong potential to extend the application of these methods beyond the machine technology project course. By adapting these tools, institutions can evaluate lecturers across various subjects, thereby enhancing flexibility and standardization in performance assessments.

When determining the weight or importance of different evaluation criteria, particularly those based on input from school administrators, methods such as PIPRECIA and LOPCOW can be employed. These approaches ensure accuracy and adaptability by aligning evaluations with the specific context and priorities of the academic environment.

In summary, this study offers a comprehensive perspective on lecturer evaluation within the machine technology project course and lays the groundwork for broader applications across other educational domains.

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Ethical Approval: The study adheres to the ethical guidelines for conducting research.

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