Simple Additive Weight Algorithm to Determine Lecturer Competency in Hybrid Learning Approach

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ABSTRAK

Seiring dengan berlangsungnya proses vaksinasi COVID-19, pandemi ini mulai mereda. Semua lembaga pendidikan di Indonesia mulai beralih dari pembelajaran online ke pembelajaran hybrid (hybrid learning). Salah satu faktor penting dalam kegiatan belajar-mengajar adalah kemampuan mengajar dosen. Namun, masih ada beberapa mahasiswa yang merasa kurang puas dengan proses pembelajaran karena kurangnya kemampuan mengajar dari dosen. Hal ini diperparah oleh kurangnya familiaritas dosen dan mahasiswa dengan sistem pembelajaran hybrid learning. Oleh karena itu, tujuan dari penelitian ini adalah menemukan model evaluasi kemampuan mengajar dosen yang sesuai dengan pendekatan pembelajaran saat ini, yaitu hybrid learning approach. Data yang digunakan dalam penelitian ini berasal dari kuesioner yang diisi oleh seluruh mahasiswa Universitas Dian Nuswantoro setiap tahun sebelum Ujian Akhir Semester (UAS). Kuesioner terdiri dari 10 pertanyaan mengenai proses pembelajaran hybrid di tahun akademik 2022/2023. Mahasiswa memberikan jawaban menggunakan skala Likert 4 poin, yang terdiri dari "Sangat Setuju", "Setuju", "Tidak Setuju", dan "Sangat Tidak Setuju". Respon dari mahasiswa dikelompokkan berdasarkan mata kuliah yang diajar oleh dosen. Penilaian kemampuan dosen direpresentasikan oleh 2 aspek, yaitu kemampuan mengajar dan penguasaan materi. Setiap aspek penilaian dosen terdiri dari 5 pertanyaan dalam kuesioner. Metode yang digunakan untuk mengevaluasi kemampuan mengajar dosen adalah Decision Support System (DSS) yang dikombinasikan dengan Simple Additive Weight (SAW). Ditemukan bahwa mahasiswa rata-rata cukup puas terhadap kualitas kuliah. Selain itu, dosen dengan nilai evaluasi yang tinggi cenderung memiliki sedikit jumlah mahasiswa.

As the COVID-19 vaccination process continues, the pandemic is starting to subside. All educational institutes in Indonesia are starting to transition from online learning to hybrid learning. One crucial factor in the learning process is the competency of the lecturers. However, some students still feel dissatisfied with the learning process due to the lack of competence from the lecturers. This is exacerbated by the students and lecturers' lack of familiarity with the hybrid learning system. Therefore, the aim of this research is to find a fair evaluation model for the lecturer's competency that is suitable for the current hybrid learning approach. The data used in this research comes from questionnaires filled out by all students of Dian Nuswantoro University every year before the Final Semester Exam (UAS). The questionnaire consists of 10 questions regarding the hybrid learning process in the academic year of 2022/2023. Students provide their answers using a 4-point Likert scale, consisting of "Strongly Agree," "Agree," "Disagree," and "Strongly Disagree." The responses from students are grouped based on the courses/classes taught by the lecturers. The evaluation of lecturers' competency is represented by two aspects: knowledge mastery and teaching skill. Each aspect of the lecturers' evaluation consists of 5 questions in the questionnaire. The method used to evaluate the lecturers' competency is the Decision Support System (DSS) algorithm combined with Simple Additive Weight (SAW). Result shows that students are mostly pleased with the quality of the lectures presented. Furthermore, lecturers with high evaluation scores tend to have a small number of students.

Kata Kunci – Hybrid Learning, Decision Support System, Simple Additive Weighting,

1. INTRODUCTION

In January 2020, COVID-19 emerged from the Wuhan Animal Market in China. Due to the government's slow reaction and the high transmissibility of COVID-19, it quickly spread worldwide. As people began to get vaccinated, the impact of the COVID-19 pandemic gradually diminished. Consequently, students and teachers worldwide sought to transition from online learning to hybrid learning. Hybrid learning is an educational approach that combines the advantages of both online and offline learning. In hybrid learning, for instance, if a class typically meets three times a week, one or two of those meetings are replaced with online sessions or activities, while the remainder are conducted in-person (Dwijonagoro & Suparno, 2019). The implementation of hybrid learning provides students and lecturers with additional flexibility and time. This extra space and time help students develop independence in researching and processing information, while still having the option to contact lecturers through online messaging systems (Meydanlioglu & Arikan, 2014).

The COVID-19 pandemic and the introduction of hybrid learning is a novel experiences for all of us. It is understandable to feel unprepared and unfamiliar with these circumstances. As leaders

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in the classroom, lecturers play a vital role in guiding and supporting their students in mastering this new approach. Furthermore, research (Jasmani & Paeno, 2019; Yulian, 2021) highlights the substantial influence lecturers have on students' overall learning experience during lectures. These two challenges, the transition to hybrid learning and the influence of lecturers, compound each other and can lead to lower student engagement, lack of motivation, and ultimately, unsatisfactory grades. It’s imperative for lecturers to proactively adapt their teaching methods and enhance their understanding of hybrid learning to ensure a positive and productive learning environment for their students.

As the saying goes, "What cannot be measured, cannot be improved.", recognizing the importance of assessing and enhancing lecturer performance, our objective is to establish a fair evaluation model using a Decision Support System in conjunction with the Simple Additive Weight algorithm.

Decision Support System (DSS) is a computer-based information system designed to assist individuals or organizations in making effective decisions.The primary goal of a decision support system is to enhance the decision-making process by providing structured and unstructured data, as well as tools for analysis, modeling, and visualization (Gupta et al., 2022; Puspa, 2019).

Simple Additive Weight (SAW) or a Weighted Sum Model is a multi-criteria decision-making technique that assigns weights to different criteria and computes an overall score for each alternative based on the weighted sum of criteria values (Anggraini & Sihotang, 2019).

By implementing this evaluation model, this research can identify specific areas where lecturers may need improvement and take proactive measures to enhance their understanding and effectiveness in the context of hybrid learning. This model will provide valuable insights and enable targeted interventions to support lecturers in delivering high-quality education and fostering optimal learning outcomes for students (Mulyani et al., 2020).

2. Research Methodology

The steps conducted in this research for evaluating lecturers performance in hybrid learning method are as shown in Figure 1:

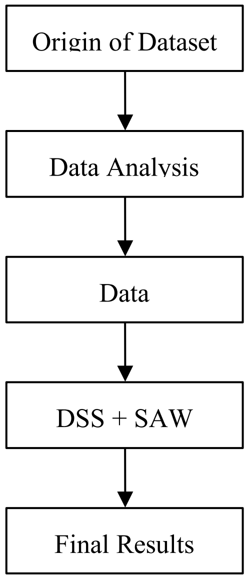

Figure 1. Flow of data in this research

A. Origin of Dataset

The dataset used in this study was generated from a semesterly questionnaire administered to a total of 3143 students over 224 unique classes. The raw dataset has over 20.000 entries due to students attending multiple classes at once. The questionnaire consists of 10 questions that aimed to assess the students' experience of lectures based on two aspects: the lecturer's knowledge mastery and teaching skills. The students responded to the questionnaire using a 4-point Likert scale and its numerical equivalent, which is included in Table 1 below (Sumekto & Setyawati, 2018; Supriadi et al., 2021) :

Table 1. Flow of data in this research

Likert Scale in Questionnaire	Numerical Equivalent
Strongly Disagree	1
Disagree	2
Agree	3
Strongly Agree	4

Once the semester ended and all the participants had completed the questionnaire, the dataset was collected and converted into a CSV

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format, making it ready for further processing and analysis.

B. Dataset Analysis

Cronbach Alpha test is a test measuring the equivalence of sets of items against a construct in an instrument (Setyowati et al., 2023; Taber, 2018). In this research, the items refers to the 10 questions being asked to the students. The constructs refers to the aspects that are evaluated from the lecturers, which is knowledge mastery and technical skill. The questionnaire is further divided into two constructs or aspects, which are lecturers' knowledge mastery and lecturers' teaching skill. Each construct has five items or questions. The result of Cronbach Alpha test of our questionnaire dataset is shown on Table 2 below :

Table 2. Cronbach Alpha Score

Aspect or Construct	Cronbach Alpha Score
Teaching Skill	0.91
Knowledge Mastery	0.89

The Cronbach Alpha score for teaching skill aspect is 0.91, and knowledge mastery aspect is 0.89. This means the equivalence of each construct in the questionnaire is very high. (Olaniyi, 2019)

C. Implement DSS SAW Algorithm into dataset

In this research, DSS and SAW algorithms are used together to evaluate lecturers performance by creating a ranking based on multiple criterias.

According to research (Arifitama, 2022; Sovia et al., 2020), the calculation steps using the Simple Additive Weighting (SAW) method:

1. Determining Alternative
2. Determining the criteria to be used as a reference in decision making
3. Determine the preference weight for each criterion
4. Determine the Match Value of each criterion
5. Make a decision matrix obtained from the suitability rating for each alternative with each criterion
6. Perform the normalization step of the decision matrix by calculating the value of the normalized performance rating from the alternative on the criteria
7. The result of normalization forms a normalized matrix
8. The final result of the preference value is obtained from the sum of the normalized matrix row elements with the preference weights corresponding to the matrix column elements .

3. Results and Discussion

Below is the step-by-step calculation of DSS SAW algorithm on the questionnaire dataset.

A. Alternative

The alternative for this research is the combination between the students' number and the class they're enrolled in. Combining class code and student ID ensures every alternative is unique. Table 3 shows the alternative code for each student.

Table 3. Alternative Decision

Alternative Code	Student ID
A1	A11.2017.1xxx - AF201703
A2	A11.2017.10xxx - AF201703
A3	A11.2018.11xxx - AF201703
A4	A11.2019.11xxx - AF201703
A5	A11.2019.11xxx - AF201703
...	...
A20093	A11.2020.80xxx - A11.54508
A20094	A11.2020.80xxx - A11.54812
A20095	A11.2018.11xxx - AF201704
A20096	A11.2021.13xxx - AF201704
A20097	A11.2020.13xxx - U201701

B. Aspect, Criteria and Attribute Criteria

Table 4 below shows the the 10 questions or criteria listed in the questionnaire, divided into two aspects, in which all of them are beneficial to the aspects measured.

Table 4. Criteria Decision

Criteria	Description	Aspect	Attribute
C1	Does the lecturer mastered the academic material being teached in class?	Teaching Skill	Benefit
C2	Are the examples and case studies given by the lecturer relevant to the academic materials teached in class?	Teaching Skill	Benefit
C3	Can the lecturer explain the lecture material well?	Teaching Skill	Benefit
C4	Does the lecturer provide good responses to questions from students?	Knowledge Mastery	Benefit
C5	Does the lecturer present lecture material sequentially based on Standard Academic Procedure (SAP)?	Teaching Skill	Benefit

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C6	Does the lecturer consistently arrive on time for their commitments?	Knowledge Mastery	Benefit
C7	Does the way the lecturer teach improves students' interest to learn?	Knowledge Mastery	Benefit
C8	Does the lecturer effectively manage the classroom?	Knowledge Mastery	Benefit
C9	Does the lecturer uses lecture time efficiently?	Knowledge Mastery	Benefit
C10	Does the lecturer uses proper academic reference in the teaching process?	Teaching Skill	Benefit

C. Criteria Weight

Giving weight to each criterion to determine which criteria is more or less important compared to other criterias. Table 5 contains the criteria weight suggested by Mr. Sri Winarno, as the education expert in this research.

Table 5. Criteria Weight

Criteria	Description	Aspect	Weight
C1	Does the lecturer mastered the academic material being teached in class?	Teaching Skill	1
C2	Are the examples and case studies given by the lecturer relevant to the academic materials teached in class?	Teaching Skill	3
C3	Can the lecturer explain the lecture material well?	Teaching Skill	2
C4	Does the lecturer provide good responses to questions from students?	Knowledge Mastery	3
C5	Does the lecturer present lecture material sequentially based on Standard Academic Procedure (SAP)?	Teaching Skill	4
C6	Does the lecturer consistently arrive on time for their commitments?	Knowledge Mastery	4
C7	Does the way the lecturer teach improves students' interest to learn?	Knowledge Mastery	1
C8	Does the lecturer effectively manage the classroom?	Knowledge Mastery	2
C9	Does the lecturer uses lecture time efficiently?	Knowledge Mastery	5
C10	Does the lecturer uses proper academic reference in the teaching process?	Teaching Skill	5

D. Alternative Values on Each Criterion

This shows the students' answer to the questionnaire that consists of 10 questions or criterias, represented by likert scale values listed below in Table 6

Table 6. Alternative Values

Alt	Criteria									
	c1	c2	c3	c4	c5	c6	c7	c8	c9	c10
A1	2	2	2	2	2	2	2	2	2	2
A2	4	4	4	4	4	4	4	4	4	4
A3	4	4	4	4	4	4	4	4	4	4
A4	4	4	4	4	4	4	4	4	4	4
A5	4	4	4	4	4	4	4	4	4	4
...	..	...	...	...	...	...	...	...	...	...
A20093	4	3	3	4	4	4	4	4	4	4
A20094	4	4	4	4	4	4	4	4	4	4
A20095	4	4	4	4	4	4	4	4	4	4
A20096	4	4	4	4	4	4	3	3	3	4
A20097	3	3	3	4	3	3	3	3	3	3

E. Value Normalization

Normalize each alternative values using min-max normalization. Since we only have benefit criteria, in Equation 1 is used:

$$R_{ij} = \{\frac{x_{ij}}{Max(x_{ij})}\} \quad (1)$$

R = Normalized Value

i = Index alternative

j = Index criteria

x = Alternative value

Max(x) = Maximum alternative value

Example of normalization of the first alternative (A1) is shown on Equation 2:

$$R_{11} = \frac{2}{4} = 0.5 \quad (2)$$

Result of normalization calculation on dataset is as shown in Table 7 below:

Table 7. Normalize Alternative Values

Alt	Criteria

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	c1	c2	c3	c4	c5	c6	c7	c8	c9	c10
A1	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5
A2	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0
A3	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0
A4	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0
A5	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0
...	...	...	...	...	...	...	...	...	...	...
A20093	1.0	0.75	0.75	1.0	1.0	1.0	1.0	1.0	1.0	1.0
A20094	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0
A20095	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0
A20096	1.0	1.0	1.0	1.0	1.0	1.0	0.75	0.75	0.75	1.00
A20097	0.75	0.75	0.75	1.0	0.75	0.75	0.75	0.75	0.75	0.75

F. Alternative Value Calculation

The calculation for alternative value is to sum the results of the multiplication of normalized alternative value times the respective criteria weight.

The formula in Equation 3 is used to calculate alternative values:

$$V_i = \sum_{j=1}^{n} W_j R_{ij} \tag{3}$$

V = Final value
W = Weight value
R = Normalized alternative value
n = Number of data
i = Index alternative
j = Index criteria

For example for the first alternative (A1):

$V_1 = (0.5 \times 1) + (0.5 \times 3) + (0.5 \times 2) + (0.5 \times 3) + (0.5 \times 4) + (0.5 \times 4) + (0.5 \times 1) + (0.5 \times 2) + (0.5 \times 5) + (0.5 \times 5)$

$V_1 = 0.5 + 1.5 + 1 + 1.5 + 2 + 2 + 0.5 + 1 + 2.5 + 2.5$

$V_1 = 15$

Result of final calculation on dataset is as shown in Table 8 below:

Table 8. Final Calculation Values

Alternative	Score
A1	15.00
A2	30.00
A3	30.00
A4	30.00
A5	30.00
...	...
A20093	28.75
A20094	30.00
A20095	30.00
A20096	28.00
A20097	23.25

G. Group results by lecturer name

Because lecturer's performance is evaluated, so the students' answers dataset is grouped by the student's lecturer as shown in Table 9 below:

Table 9. Final Calculation Values with Lecturer ID

Alternative	Lecturer ID	Score
A1	Respondent1	15.00
A2	Respondent1	30.00
A3	Respondent1	30.00
A4	Respondent1	30.00
A5	Respondent1	30.00
...	...	...
A20093	Respondent132	28.75
A20094	Respondent132	30.00
A20095	Respondent133	30.00
A20096	Respondent133	28.00
A20097	Respondent134	23.25

H. Calculate the summed value and student count for each lecturer

The final value of all students teached by a lecturer is summed into one value. The number of students being teached by each lecturer is also counted. Table 10 below shows the summed value and student count.

Table 10. Summed Value and Student Count

Lecturer	TotalScore	StudentCount
Respondent1	2302.75	81
Respondent10	4593.25	173
Respondent100	12141.75	438
Respondent101	8720.50	318
Respondent102	268.25	10
...	...	...
Respondent95	7058.75	270
Respondent96	183.50	7
Respondent97	6175.50	233
Respondent98	5445.75	197
Respondent99	60.00	2

I. Normalize final value by student count

Normalize the score by student count to get a fair score. Table 11 below shows the final normalized value.

Table 11. Final Normalized Value

Rank	Lecturer	TotalScore	StudentCount	NormalizedValue
1	Respondent99	60	2	30
2	Respondent81	90	3	30
3	Respondent63	60	2	30
4	Respondent62	30	1	30
5	Respondent49	30	1	30

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…	...	...	...	...
130	Respondent131	24.50	1	24.50
131	Respondent50	4552.25	186	24.47
132	Respondent55	13898	568	24.47
133	Respondent134	23.25	1	23.25
134	Respondent76	22.50	1	22.50

After all calculations are done, scatter plot and box plot diagrams are created to analyze the result, as shown in Figure 2:

Figure 2. Scatter plot of final calculation

The X axis represents the final value (normalized value) of the lecturer's performance, while the Y axis represents the number of students taught by the lecturer. Each colored dot represents a unique lecturer. The dots are mostly grouped near the middle, where the normalized value is around 26-28, and student count is around 0-300. This scatter plot resembles a normal distribution with a tiny skew to the right. For additional information, box plot is shown on Figure 3:

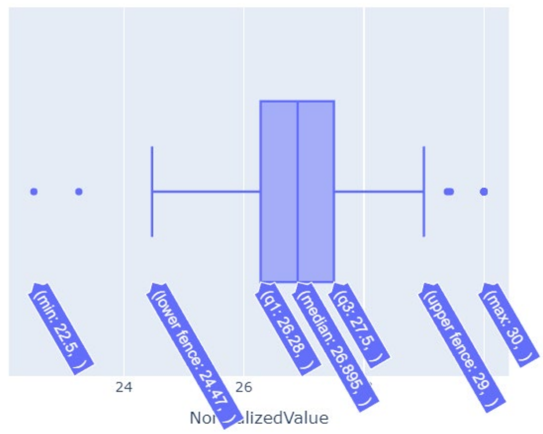

Figure 3. Box plot of final calculation

The box plot shows the true limits of the final score (normalized value). Q1 is 26.28, median is 26.895, Q3 is 27.5. The result has a relatively small spread. The box plot also shows us small amount of dots outside the lower and upper fences, which means the outliers are very minimal.

4. Conclusion

This research aims to create an evaluation model for lecturers' performance in hybrid-learning setting. Decision Support System with Simple Additive Weight is used to process the questionnaire dataset. The questionnaire dataset consists of 3143 students, spread over 224 unique classes, taught by 134 lecturers.

The conclusive findings reveal that the lecturers' performance is predominantly satisfactory. Consequently, the Simple Additive Weight-based Decision Support System (SAW-DSS) model proves to be well-suited for ranking lecturers' performance. The final performance scores range from 22.5 to 30, with a median value of 26.895. This data distribution exhibits characteristics of a near-normal distribution, albeit with a slight rightward skew. In comparison to prior research, our results achieve a comparable level of satisfaction, owing to the model's user-friendly interface, streamlined process, and swift execution.

However, its important to note that the DSS SAW algorithm is an afterthought to the questions listed in the questionnaire. This research would yield better results if the questions are tailored specifically to measure certain aspects of the lecturers. (Constantinou et al., 2016)

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