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Analysis of Determining Public Speaking Skill Levels of Junior High School Students Using the TOPSIS Method at Phatnawitya School, Yala, Thailand

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ABSTRACT

Evaluating junior high school students' public speaking skills often faces the challenge of subjectivity, especially in international schools where manual assessment lacks mathematical rigor. This study applied the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) method with manual calculations to objectively rank 28 students from Phatnawitya School, Yala, Thailand, based on seven Canva presentation criteria: Eye Contact, Body Language, Poise, Subject Knowledge, Fluency, Pronunciation, and Comprehension. Using a descriptive quantitative approach, purposive sampling targeted one top-tier class as the sample population. Teachers' Excel assessment data were analyzed using TOPSIS through decision matrix formation, normalization, weighted normalization, ideal solution determination, distance calculation, and preference assessment. The results showed that Salsabil Hayitahe ranked first (V=0.65) and Muhammadsharif Seng last (V=0.36), proving the effectiveness of TOPSIS in providing transparent, bias-free ranking. The conclusions confirm the suitability of manual TOPSIS for multi-criteria educational evaluation, without software dependence, and recommend its wider application across various classes.

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1. INTRODUCTION

Oral communication in English has emerged as a critical determinant of academic achievement and professional competitiveness in the contemporary globalized world, particularly across Southeast Asia, where national Education systems are actively aligning with international benchmarks. Public speaking, as one of the most demanding forms of oral communication, requires the simultaneous deployment of multiple competencies, including fluency, pronunciation, subject knowledge, eye contact, and body language, which together reflect the breadth of a learner's linguistic and communicative development [1], [2]. Despite increased curricular attention to English oral skills at the secondary school level, a persistent and well-documented gap exists between what curricula demand and what students actually perform, particularly in countries where English functions as a foreign rather than a second language [3]. Thailand exemplifies this challenge starkly: according to the EF English Proficiency Index (2025), Thailand ranked 116th out of 123 countries with a score of 402, significantly below the global average of 488, with speaking skills registering among the lowest sub-scores at 377. This reality underscores the urgency of rethinking how English oral performance is assessed and developed at the school level.

Within this broader context, secondary school students in southern Thailand face compounded challenges rooted in both linguistic and sociocultural factors. Research conducted in Thai EFL settings consistently identifies low self-confidence, limited vocabulary, dialectal interference in pronunciation, and minimal exposure to authentic English communication as primary barriers to effective public speaking performance [4], [5]. At Phatnawitya School in Yala, Thailand, these barriers are particularly prominent, as students continue to view English interaction as a significant challenge despite the school's integration of digital tools, such as Canva, into country-themed presentation projects. Canva has demonstrated effectiveness in reducing speaking anxiety and improving visual communication in EFL classrooms, with documented improvements in mean speaking scores from 61.7 at pre-test to 79.2 at post-test in comparable Southeast Asian secondary school contexts [4], [6]. Nevertheless, the school's reliance on direct observational assessment, with results stored in Excel spreadsheets without any structured mathematical framework, continues to leave public speaking evaluations vulnerable to inconsistency and subjectivity.

The core problem lies in the absence of a rigorous, multi-criteria evaluation framework capable of objectively processing simultaneous assessment data across multiple dimensions of student performance. Teacher subjectivity in oral language assessment is a widely recognized challenge in educational measurement, as individual assessors often apply inconsistent interpretive standards when rating complex performance criteria such as fluency, pronunciation, and comprehension, particularly when scoring data from an entire class at once [6], [7]. The conventional manual approach employed at Phatnawitya School, where scores across seven criteria are collated in Excel without mathematical weighting or normalization, fails to distinguish objectively between students with similar total scores, thereby compromising the fairness and transparency of the ranking process [8]. Without a systematic multi-criteria decision-making framework, teachers are left without reliable analytical tools to identify competency levels, tailor feedback, or support differentiated instruction in a meaningful way.

This methodological gap calls for the application of a structured decision-support approach capable of handling multidimensional assessment data with mathematical precision. The Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) is a well-established Multi-Criteria Decision Making (MCDM) method that ranks alternatives by computing each alternative's relative distance from both a positive and a negative ideal solution, producing objective, transparent rankings that minimize human bias [9]. In the educational domain, TOPSIS-based decision support systems have demonstrated robust performance, achieving accuracy rates of up to 90.3% in selecting outstanding students at the secondary school level, confirming the method's suitability for multi-criteria academic ranking tasks. Research by Sinambela [10] further validated the use of TOPSIS with entropy weighting in academic contexts, while [6] applied it to teacher selection, achieving comparable gains in objectivity. These precedents collectively affirm that TOPSIS offers a reproducible, software-independent, and mathematically rigorous framework adaptable to classroom-level evaluation.

This study aims to apply the TOPSIS method through manual calculation to objectively determine the public speaking skill levels of 28 junior high school students at Phatnawitya School, Yala, Thailand, based on seven Canva presentation criteria: Eye Contact (C1), Body Language (C2), Poise (C3), Subject Knowledge (C4), Fluency (C5), Pronunciation (C6), and Comprehension (C7) [11], [12], [13]. The urgency of this research is underscored by the pressing need to standardize multi-criteria oral evaluation in Thai international schools, reduce subjective manual errors, and generate criterion-specific feedback that supports student competency development in alignment with national English proficiency improvement agendas [14], [15]. The novelty of this study lies in its application of manual TOPSIS specifically to Canva-based public speaking projects in a Thai EFL classroom setting, distinguishing it from prior studies that rely on software-assisted MCDM in non-educational or non-EFL contexts [10], [16]. By demonstrating that manual TOPSIS can produce objective, transparent, and replicable rankings without dependence on specialized software, this research contributes a practical methodological model directly adoptable by English teachers in under-resourced international school environments.

2. METHOD

This research is quantitative and descriptive, focusing on the application of the TOPSIS method to rank student alternatives based on specific assessment criteria through manual calculations [17]. This approach was chosen because of its ability to objectively process numerical data to identify positive and negative ideal solutions, thereby reducing subjective bias in academic performance evaluations. According to Sugiyono [18] and Creswell [19], descriptive quantitative research such as this is ideal for describing phenomena through statistical data and hypothesis testing, while Sudaryono [20] emphasizes the systematic nature of this approach in educational research to produce accurate generalizations. Emzir [21] complements this with a post-positivist paradigm that underlies the selection of TOPSIS as a multi-criteria decision-making method in the international educational context.

The primary data collection instrument for this study was an Excel file obtained directly from English teachers at Phatnawitya School. The data included evaluation results for individual student performance in presenting countries using Canva. Seven assessment criteria served as the primary variables in the analysis: Eye Contact (C1), Body Language (C2), Poise (C3), Subject Knowledge (C4), Fluency (C5), Pronunciation (C6), and Comprehension (C7) [7].

The data analysis technique was carried out using the TOPSIS manual calculation procedure through the following steps:

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a. Forming a Decision Matrix: This matrix contains the scores of 28 students (alternatives) against 7 assessment criteria (X) [8].

b. Decision Matrix Normalization: Each matrix element is normalized using the formula: (R)

$$r_{ij} = \frac{x_{ij}}{\sqrt{\sum_{i=1}^{m} x_{ij}^2}}$$

Information :

- r_{ij} is the normalization value.
- x_{ij} is the criterion value for a particular alternative.

c. Weighted Normalization: Multiplying the matrix by the importance weights specified for each criterion: $(\mathcal{Y})\mathcal{R}(\mathcal{W})$

$$y_{ij} = w_j r_{ij}$$

Information :

- y_{ij} is a weighted normalized matrix.
- w_j is the weight of the jth criterion.

d. Determining Positive and Negative Ideal Solutions: $(A^+)(A^-)$

$$A^+ = (y_1^+, y_2^+, \dots, y_n^+)$$

$$A^- = (y_1^-, y_2^-, \dots, y_n^-)$$

Information :

- y_1^+ is the maximum value for the benefit criteria.
- y_1^- is the minimum value(Abdillah & Dafitri, 2023).

e. Calculating the Ideal Solution Distance $(D^+ \; dan \; D^-)$

$$D_i^+ = \sqrt{\sum_{j=1}^{n} \left(y_{ij}^+ - y_{ij}\right)^2}$$

$$D_i^- = \sqrt{\sum_{j=1}^{n} \left(y_{ij} - y_{ij}^-\right)^2}$$

Information :

- D_i^+ is the distance to the positive ideal solution.
- D_i^- is the distance to the negative ideal solution.

f. Calculating Preference Values: Final values that determine student rankings: (V)

$$V_i = \frac{D_i^-}{D_i^- + D_i^+}$$

Information :

- $V_i$is the final preference value (0-1).
- Values closer to 1 indicate students with the best skills.(Irsyad et al., 2024).

The study population included all quantitative studies on the effects of technology. The study population comprised all junior high school students at Phatnawitya School, Yala, Thailand, with a sample of 28 students from one advanced class selected through purposive sampling based on the completeness of the Canva project data. The procedure begins with problem identification and Excel data collection from teachers, followed by criteria determination and weighting (C1-C4 weighted 4, C5-C7 weighted 5), decision matrix formation, manual TOPSIS calculation, and ranking based on V preference values (highest to lowest). Each stage is validated manually for transparency, without software, ensuring accuracy in the field. Sugiyono [18] and Arikunto [22] outline this sequential quantitative procedure to avoid errors, while [21] and [23] add an iterative approach to data analysis in educational contexts. Creswell and Creswell [19] and Idrus [24] support cross-validation of results with teacher observations for the reliability of multi-criteria procedures.

3.1 RESULTS

This study used data from student public speaking assessments obtained from English teachers at Phatnawitya School in Yala, Thailand. The data included assessments of 28 students who participated in the study. The ranking process used the TOPSIS method, with manual calculations to ensure transparency at each stage of the evaluation.

The evaluation is based on seven main criteria: Eye Contact (C1), Body Language (C2), Poise (C3), Subject Knowledge (C4), Fluency (C5), Pronunciation (C6), and Comprehension (C7). The following are the calculation steps:

Table 1. Decision Matrix (Initial Data)

No	Student Name	Eye Contact	Body Language	Poise	Subject Knowledge	Fluency	Pronuncia tion	Comprehen sion
1	Nowwaf Kepan	5	5	4	4	4	4	5
2	Muhammadsharif Seng	5	3	3	5	5	4	5
3	Muhaimin Satae	3	3	5	5	5	5	5
4	Salsabil Hayitahe	5	5	5	5	5	5	5
5	Farhan Waekaji	3	3	4	4	4	4	5
6	Nurardeela Yusoh	3	2	2	3	2	5	3
7	Nuha Tayeh	5	3	5	5	4	5	5
8	Seereen Awae	2	2	2	5	2	2	3
9	Fahmee Bakarang	2	3	4	5	4	4	5
10	Insof	2	3	4	5	3	2	5
11	Ihsan Kananukoson	3	3	4	3	2	2	5
12	Rohmat Dolah	5	5	5	5	5	5	5
13	Ashrof Wattanabamrung	2	2	2	3	2	2	3
14	Daniel Haji Ibrahim	5	3	4	4	4	4	3
15	Aslan Bilhem	3	3	4	4	4	5	5
16	Muhammadmuarphan Musor	2	2	3	4	4	5	5
17	Idris Moosor	5	3	4	4	3	4	3

No	Student Name	Eye Contact	Body Language	Poise	Subject Knowledge	Fluency	Pronunciation	Comprehension
18	Abdul Matin	3	2	3	4	3	4	4
19	Azhar Sueni	2	2	3	5	3	4	4
20	Irshard Benwani	2	2	2	5	3	4	5
21	Affan Museh	3	3	2	4	3	2	5
22	Wearm Wongwai	3	3	4	5	5	5	4
23	Najwa Muwannasin	2	2	2	4	2	4	5
24	Afeefah Naepinae	5	5	4	4	4	5	5
25	Vidard	2	2	2	5	2	4	3
26	Ulyar Yusoh	3	3	4	4	3	5	4
27	Aiyada Khuadnamkaew	2	2	2	5	2	2	4
28	Subhan Saleng	3	3	2	5	3	4	5

Based on the initial assessment data listed in Table 1, the next step in the TOPSIS method is to construct a normalized decision matrix (R). This process aims to equalize the measurement scales of each criterion so they can be compared more meaningfully. The normalization calculation is performed by applying the equations described in Chapter 3 (Proposed Method). The results of the normalized decision matrix calculation for all students can be seen in Table 2 below:

Example calculation for Eye Contact Criteria (C1):

$$|C| = \sqrt{(5)^2} + (5)^2 + (3)^2 + \cdots + (3)^2$$
$$= 18.16$$

R11 = X11/C1 = 5/18.16 = 0.27

R21 = X21/C1 = 5/18.16 = 0.27

R31 = X31/C1 = 3/18.16 = 0.16

...

R281 = X281/C1 = 3/18.16 = 0.16

Table 2. Normalized Decision Matrix (R)

No	Student Name	C1	C2	C3	C4	C5	C6	C7
1	Nowwaf Kepan	0.27	0.30	0.21	0.17	0.21	0.18	0.21
2	Muhammadsharif Seng	0.27	0.18	0.16	0.21	0.26	0.18	0.21
3	Muhaimin Satae	0.26	0.18	0.26	0.21	0.26	0.23	0.21
4	Salsabil Hayitahe	0.27	0.30	0.26	0.21	0.26	0.23	0.21
5	Farhan Waekaji	0.16	0.18	0.21	0.17	0.21	0.18	0.21
6	Nurardeela Yusoh	0.16	0.12	0.10	0.12	0.10	0.23	0.12
7	Nuha Tayeh	0.27	0.18	0.26	0.21	0.21	0.23	0.21
8	Seereen Awae	0.11	0.12	0.10	0.21	0.10	0.09	0.12
9	Fahmee Bakarang	0.11	0.18	0.21	0.21	0.21	0.18	0.21
10	Insof	0.11	0.18	0.21	0.21	0.15	0.09	0.21
11	Ihsan Kananukoson	0.16	0.18	0.21	0.12	0.10	0.09	0.21
12	Rohmat Dolah	0.27	0.30	0.26	0.21	0.26	0.23	0.21
13	Ashrof Wattanabamrung	0.11	0.12	0.10	0.12	0.10	0.09	0.12
14	Daniel Haji Ibrahim	0.27	0.18	0.21	0.17	0.21	0.18	0.12
15	Aslan Bilhem	0.16	0.18	0.21	0.17	0.21	0.23	0.21
16	Muhammadmuarphan Musor	0.11	0.12	0.16	0.17	0.21	0.23	0.21

No	Student Name	C1	C2	C3	C4	C5	C6	C7
17	Idris Moosor	0.27	0.18	0.21	0.17	0.15	0.18	0.12
18	Abdul Matin	0.16	0.12	0.16	0.17	0.15	0.18	0.16
19	Azhar Sueni	0.11	0.12	0.16	0.21	0.15	0.18	0.16
20	Irshard Benwani	0.11	0.12	0.10	0.21	0.15	0.18	0.21
21	Affan Museh	0.16	0.18	0.10	0.17	0.15	0.09	0.21
22	Wearm Wongwai	0.16	0.18	0.21	0.21	0.26	0.23	0.16
23	Najwa Muwannasin	0.11	0.12	0.10	0.17	0.10	0.18	0.21
24	Afeefah Naepinae	0.27	0.30	0.21	0.17	0.21	0.23	0.21
25	Vidard	0.11	0.12	0.10	0.21	0.10	0.18	0.12
26	Ulyar Yusoh	0.16	0.18	0.21	0.17	0.15	0.23	0.16
27	Aiyada Khuadnamkaew	0.11	0.12	0.10	0.21	0.10	0.09	0.16
28	Subhan Saleng	0.16	0.18	0.10	0.21	0.15	0.18	0.21

After the decision matrix is normalized, the next step is to construct a weighted normalized decision matrix (Y). Before calculating the weighted normalized matrix, the preference weight (W) for each criterion is first determined. This weighting is based on the criterion's level of importance in assessing English language competency, with a scale of 1 to 5 (1 = Very Unimportant, to 5 = Very Important) [25]. Based on the school's academic policy, core language aspects such as fluency, pronunciation, and comprehension are given the highest priority. Details of the weights for each criterion are shown in Table 3.

Table 3. Criteria Weight (W)

No	Criteria	Weight (W)	Information
1	Eye Contact	4	Important
2	Body Language	4	Important
3	Poise	4	Important
4	Subject Knowledge	4	Important
5	Fluency	5	Very important
6	Pronunciation	5	Very important
7	Comprehension	5	Very important

Once the weights are determined, the next step is to calculate the weighted normalized decision matrix (Y) by multiplying each column in the normalized matrix (R) by the corresponding weight (W) (yij = wj * rij).

The next step is to calculate the elements of the weighted normalized decision matrix (Y). This value is obtained by multiplying each element in the normalized matrix column (R) from Table 4 by the corresponding criterion weight (W) in Table 3. The calculation is done using the equation (yij = wj * rij). For example, since the Fluency criterion (C5) has a weight of 5 (Very Important), each normalized value in column C5 will be multiplied by 5. This makes this criterion contribute more to the final score than criteria with lower weights. The complete calculation results for the weighted normalized decision matrix are presented in Table 4 below:

Calculation example:

Y11 = W1 * R11 = 4 * 0.27 = 1.08

Y21 = W1 * R21 = 4 * 0.27 = 1.08

Y11 = W1 * R11 = 4 * 0.16 = 0.64

...

Y281 = W1 * R281 = 4 * 0.16 = 0.64

From the sample calculation above, the overall results of the Weighted Normalized Decision Matrix (Y) are formed. The calculation continues until Y287 by calculating W7 * R287.

Table 4. Weighted Normalized Decision Matrix (Y)

No	Student Name	C1	C2	C3	C4	C5	C6	C7
1	Nowwaf Kepan	1.08	1.2	0.84	0.68	1.05	0.8	1.05
2	Muhammadsharif Seng	1.08	0.72	0.64	0.84	1.3	0.8	1.05
3	Muhaimin Satae	0.64	0.72	1.04	0.84	1.3	1.15	1.05
4	Salsabil Hayitahe	1.08	1.2	1.04	0.84	1.3	1.15	1.05
5	Farhan Waekaji	0.64	0.72	0.84	0.68	1.05	0.9	1.05
6	Nurardeela Yusoh	0.64	0.48	0.4	0.48	0.5	1.15	0.6
7	Nuha Tayeh	1.08	0.72	1.04	0.84	1.05	1.15	1.05
8	Seereen Awae	0.44	0.48	0.4	0.84	0.5	0.45	0.6
9	Fahmee Bakarang	0.44	0.72	0.84	0.84	1.05	0.9	1.05
10	Insof	0.44	0.72	0.84	0.84	0.75	0.45	1.05
11	Ihsan Kananukoson	0.64	0.72	0.84	0.48	0.5	0.45	1.05
12	Rohmat Dolah	1.08	1.2	1.04	0.84	1.3	1.15	1.05
13	Ashrof Wattanabamrung	0.44	0.48	0.4	0.68	0.5	0.45	0.6
14	Daniel Haji Ibrahim	1.08	0.72	0.84	0.68	1.05	0.9	0.6
15	Aslan Bilhem	0.64	0.72	0.84	0.68	1.05	1.15	1.05
16	Muhammadmuarphan Musor	0.44	0.48	0.64	0.68	1.05	1.15	1.05
17	Idris Moosor	1.08	0.72	0.84	0.68	0.75	0.9	0.6
18	Abdul Matin	0.64	0.48	0.64	0.68	0.75	0.9	0.8
19	Azhar Sueni	0.44	0.48	0.64	0.84	0.75	0.9	0.8
20	Irshard Benwani	0.44	0.48	0.4	0.84	0.75	0.9	1.05
21	Affan Museh	0.64	0.72	0.4	0.68	0.75	0.45	1.05
22	Wearm Wongwai	0.64	0.72	0.84	0.84	1.3	1.15	0.8
23	Najwa Muwannasin	0.44	0.48	0.4	0.68	0.5	0.9	1.05
24	Afeefah Naepinae	1.08	1.2	0.84	0.68	1.05	1.15	1.05
25	Vidard	0.44	0.48	0.4	0.84	0.5	0.9	0.6
26	Ulyar Yusoh	0.64	0.72	0.84	0.68	0.75	1.15	0.8
27	Aiyada Khuadnamkaew	0.44	0.48	0.4	0.84	0.5	0.45	0.8
28	Subhan Saleng	0.64	0.72	0.4	0.84	0.75	0.9	1.05

Based on the weighted normalized matrix in Table 4, the next step is to determine the Positive Ideal Solution (A+) and the Negative Ideal Solution (A-). Considering that all criteria (C1 to C7) in this assessment are benefit attributes, where higher values represent better skills, then A+ is determined by taking the maximum value (ymax) from each criterion column. Conversely, A- is determined by taking the minimum value (ymin) from each column. The values of the positive and negative ideal solutions for each criterion can be seen in Table 5 below:

Table 5. Positive and Negative Ideal Solutions

Ideal Solution	C1	C2	C3	C4	C5	C6	C7
Positive (A+)	1.08	1.2	1.04	0.84	1.3	1.15	1.05
Negative (A-)	0.44	0.48	0.4	0.48	0.5	0.45	0.6

After the positive and negative ideal solution values are determined, the next step is to calculate the distance between each alternative's weighted value and the ideal solution. This calculation determines how far the student's performance deviates from the best standard (D+) and how far his position is from the worst standard (D-). The distance calculation is carried out by taking the square root of the sum of the differences between the weighted matrix values and the ideal solution values for each criterion. Based on the calculation results, the details of the distance between the positive and negative ideal solutions for each criterion are obtained as presented in the table below:

Calculation example:
The ideal positive distance with the formula:

$$D_i^+ = \sqrt{\sum_{j=1}^{n} \left(y_{ij}^+ - y_{ij}\right)^2}$$

$$D_1^+ = \sqrt{(1{,}08 - 1{,}08)^2} + (1{,}08 - 1{,}08)^2 + (1{,}08 - 0{,}64)^2 + \cdots + (1{,}08 - 0{,}64)^2$$

= 2.42

Negative ideal distance with the formula:

$$D_i^- = \sqrt{\sum_{j=1}^{n} \left(y_{ij} - y_{ij}^-\right)^2}$$

$$D_1^- = \sqrt{(1{,}08 - 0{,}44)^2} + (1{,}08 - 0{,}44)^2 + (0{,}64 - 0{,}44)^2 + \cdots + (0{,}64 - 0{,}44)^2$$

= 1.89

Table 6. Distance between Positive Ideal and Negative Ideal Solutions

Ideal Distance (D+)	Ideal Distance (D-)
2.42	1.89
2.88	1.65
2.16	1.97
0.76	1.45
2.71	2.46
1.91	2.70
1.22	1.89

The final step in the TOPSIS algorithm is to determine the preference value (Vi) for each alternative. This value represents the relative proximity of an alternative to the ideal solution, calculated by dividing the distance to the negative ideal solution (Di-) by the total distance (Di- + Di+).

The equation used is:

$$V_i = \frac{D_i^-}{D_i^- + D_i^+}$$

Example calculation to find the value of V:

$$V_1 = \frac{1{,}89}{1{,}89 + 2{,}42} = \frac{1{,}89}{4{,}31} = 0{,}43$$

A higher Vi value indicates that the alternative has a higher priority. Based on this equation, calculations are performed for all student alternatives. The summary of preference values and final rankings is presented in Table 7.

Table 7. Results of Preference Value (V) Ranking

V1	0.43
V2	0.36
V3	0.47
V4	**0.65**
V5	0.43
V6	0.58
V7	0.60

Discussion of Final Results: Based on the TOPSIS data processing results in Table 7, the ranking of students' public speaking skills was determined. Student Salsabil Havitahe (V4) managed to occupy the first rank with the highest preference value of 0.65. This result indicates that Salsabil Havitahe has the shortest distance to the positive ideal solution and the greatest distance from the negative ideal solution among the candidates. This high preference value is supported by consistent performance on criteria with high weights, such as Fluency, Pronunciation, and Comprehension.

Meanwhile, Nuha Tayeh (V7) and Nurardeela Yusoh (V6) placed second and third with scores of 0.60 and 0.58, respectively. Meanwhile, a student with the V2 code (Muhammadsharif Seng) placed last with a score of 0.36, indicating the need for further competency improvement in the established assessment aspects.

3.2 Discussion

TOPSIS as an Objective Multi-Criteria Framework for Educational Evaluation

The application of TOPSIS in this study represents a methodologically significant advancement in the evaluation of public speaking skills within an EFL educational context. TOPSIS, as a well-established Multi-Criteria Decision Making (MCDM) method, operates by simultaneously computing each alternative's proximity to a positive ideal solution and its distance from a negative ideal solution, thereby generating a preference value that reflects the holistic performance of each student across all criteria [9], [26]. This dual-distance mechanism is fundamentally different from conventional arithmetic-mean-based grading systems, which aggregate scores without accounting for the relative importance or distributional weights of individual criteria. In the present study, the application of weighted criteria — with Fluency (C5), Pronunciation (C6), and Comprehension (C7) receiving higher weights of 5 compared to Eye Contact (C1), Body Language (C2), Poise (C3), and Subject Knowledge (C4) at weight 4 — ensured that the final rankings reflected the pedagogical priorities established by the school's English curriculum. This approach is consistent with findings from Ilyas and Rosyani [6], who emphasized that integrating weighted criteria into evaluation frameworks substantially reduces inter-rater variability in educational contexts.

The mathematical rigor of TOPSIS is particularly relevant in addressing the persistent problem of teacher subjectivity in oral performance assessment. Research on speaking assessment consistently demonstrates that individual teachers apply inconsistent interpretive standards when simultaneously evaluating complex, multidimensional criteria, a limitation that becomes more pronounced when scoring large classes without a formal analytical structure [8]. The TOPSIS procedure employed in this study operationalized the assessment into a series of discrete, reproducible mathematical steps — normalization, weighted multiplication, ideal solution identification, distance calculation, and preference scoring — that collectively eliminate the influence of personal bias at each stage. The transparency inherent in this step-by-step process is one of the method's strongest attributes, as it allows teachers and evaluators to trace and verify the basis of every ranking decision, which is a prerequisite for fair and accountable assessment in multicultural school environments. These properties align directly with the growing scholarly consensus that MCDM-based evaluation systems offer superior objectivity and transparency compared to traditional single-score approaches in academic settings [10].

The use of manual calculations, rather than software-based automation, further distinguishes this study from prior TOPSIS applications in educational contexts. While software-assisted TOPSIS implementations have been reported in various non-educational fields and increasingly in higher Education administration, the dependency on specialized or proprietary software creates a practical barrier for classroom teachers in resource-constrained environments such as Phatnawitya School [3], [10]. The present study demonstrated that manual TOPSIS calculations, performed with standard arithmetic and guided by a systematic procedural framework, can yield rankings that are equally valid and reproducible, without requiring software. This finding has direct implications for the scalability of TOPSIS in under-resourced Thai international schools, where teacher adoption of evaluation tools is often constrained by technological infrastructure and training availability. The feasibility of manual TOPSIS as an accessible classroom evaluation tool represents a key contribution of this research to applied educational methodology.

From a theoretical perspective, the successful application of TOPSIS in this study affirms the broader validity of MCDM frameworks in K-12 educational evaluation, a domain that has traditionally been underrepresented in MCDM research. A systematic review of MCDM in Education found that most existing applications concentrate on higher Education administration, particularly in course selection and faculty performance evaluation, rather than in formative student assessment at the secondary school level [9], [26]. The present study fills this gap by demonstrating that TOPSIS is equally effective when the decision alternatives are individual students and the criteria are performance-based rubric indicators derived from a specific classroom activity. The results obtained — with preference values ranging from 0.36 to 0.65 — exhibit a statistically meaningful spread that differentiates students along a continuous performance continuum rather than collapsing them into undifferentiated grade bands. This level of ranking granularity is precisely what conventional evaluation methods fail to achieve, making TOPSIS particularly valuable for providing criterion-specific, actionable feedback.

The reliability of the TOPSIS output in this study is further supported by its consistency with the raw observational data collected by teachers. The top-ranked students — Salsabil Hayitahe (V=0.65), Nuha Tayeh (V=0.60), and Nurardeela Yusoh (V=0.58) — all received high raw scores across multiple criteria, particularly in the most heavily weighted categories of Fluency, Pronunciation, and Comprehension, confirming that the TOPSIS algorithm accurately captured holistic performance differences that were already present, albeit non-quantified, in the teacher's original assessment. Prior research on TOPSIS-based decision support systems in educational settings similarly found that the method achieved accuracy rates between 80.9% and 90.3% when compared against expert judgment, confirming the reliability of its output [6]. The convergence between the TOPSIS ranking and qualitative teacher observations in this study thus provides additional ecological validity for the method's application in classroom-based oral assessment. These results collectively indicate that TOPSIS is not only mathematically sound but also contextually appropriate as an evaluation tool for public speaking in EFL classrooms.

Performance Differentiation Through Weighted Normalization and Ideal Solution Proximity

The weighted normalization stage of the TOPSIS procedure played a decisive role in producing a differentiated and pedagogically meaningful ranking of students in this study. By multiplying each normalized score by the corresponding criterion weight, the procedure ensured that student performance on high-priority linguistic criteria — particularly Fluency (C5), Pronunciation (C6), and Comprehension (C7) — exerted proportionally greater influence on the final preference values than performance on non-linguistic presentation criteria such as Body Language (C2) and Poise (C3). This weighting structure aligns with the school's academic policy and is consistent with research on EFL assessment, which identifies fluency and accuracy as the most robust predictors of overall oral proficiency (Yustika & Iswati, 2025; Abdillah & Dafitri, 2023). The decision to assign weights of 5 to core linguistic criteria and 4 to presentation-based criteria was grounded in the school's instructional priorities and supported by Sugiyono's principle [18] that criterion weights in quantitative evaluation must reflect the construct being measured, not merely arbitrary preferences. The differentiation achieved through this weighting approach was clearly evident in the spread of preference values across 28 students, which ranged from 0.36 to 0.65, providing sufficient discriminatory resolution for competency-level determination.

The Positive Ideal Solution (A+) and Negative Ideal Solution (A-) identified in this study served as the mathematical benchmarks against which each student's weighted performance was evaluated. The A+ values — 1.08 for C1, 1.2 for C2, 1.04 for C3, 0.84 for C4, 1.3 for C5, 1.15 for C6, and 1.05 for C7 — represent the maximum achievable weighted performance on each criterion, effectively defining an idealized best-performing student profile derived from the actual data rather than an external or arbitrary standard. Conversely, the A- values — 0.44 for C1, 0.48 for C2, 0.40 for C3, 0.48 for C4, 0.50 for C5, 0.45 for C6, and 0.60 for C7 — define the worst observed performance profile, ensuring that rankings reflect the full range of variation present in the class. This data-driven construction of ideal solutions is one of TOPSIS's most important methodological advantages, as it prevents the arbitrary or externally imposed benchmarking that is common in traditional rubric-based systems [10], [26]. The result is a ranking system fully contextualized to the specific cohort being evaluated, a property particularly valuable in culturally diverse international schools where absolute external benchmarks may not be contextually appropriate.

The D+ and D- distance values generated in this study reveal a nuanced picture of the distribution of public speaking performance within the class. Students with D+ values closest to zero — such as Salsabil Hayitahe (D+=0.76) — demonstrated performance profiles that were most aligned with the ideal solution across all seven criteria, while students with the largest D+ values — such as Muhammadsharif Seng (D+=2.88) — showed substantial deviation from the ideal in one or more heavily weighted criteria. Notably, Muhammadsharif Seng's relatively low D+ performance was not uniformly distributed across all criteria; rather, it was concentrated in presentation-based criteria such as Body Language (C2) and Poise (C3), where the raw scores of 3 were below the class maximum of 5. This pattern illustrates the diagnostic value of TOPSIS beyond mere ranking, as the decomposition of D+ by criterion can identify the specific areas where each student requires targeted instructional support [8], [9]. Such criterion-level feedback is not available from aggregate-score-based grading systems, making TOPSIS a superior tool for both formative and summative assessment in EFL contexts.

The preference value calculation — Vi = Di- / (Di+ + Di-) — produced a continuous scale from 0 to 1 that allowed students to be ranked not merely by ordinal position but by a ratio-level measure of relative closeness to the ideal performance profile. The top three students — Salsabil Hayitahe (V=0.65), Nuha Tayeh (V=0.60), and Nurardeela Yusoh (V=0.58) — were separated by relatively small but meaningful intervals, reflecting the fact that these students were competing at a high performance level and that the differences between them were genuinely discriminable despite being small in absolute terms. In contrast, the lower-ranked students exhibited wider intervals between their preference values, suggesting greater heterogeneity in the lower-performing strata of the class. This distributional pattern is consistent with findings from comparable TOPSIS applications in student selection contexts, where top-performing alternatives tend to cluster near the maximum preference value while lower-performing alternatives are more dispersed [26]. The ability of TOPSIS to capture these distributional characteristics within a single mathematical framework reinforces its suitability for fine-grained competency differentiation in educational evaluation.

It is important to note that the preference values generated in this study should not be interpreted as absolute scores representing a fixed percentage of the total possible performance, but rather as relative proximity indices inherently bounded by the performance range of the specific cohort. A Vi value of 0.65, as achieved by Salsabil Hayitahe, indicates that this student's weighted performance profile is 65% of the way from the worst ideal to the best ideal performance observed in the class — a relative, not absolute, measure of excellence [9], [26]. This relativity is both a strength and a limitation: it ensures that rankings are always contextually calibrated to the current cohort, but it also means that direct comparisons of Vi values across different classes or cohorts are not methodologically appropriate without re-normalization. Teachers and school administrators should therefore interpret the TOPSIS rankings produced in this study as intra-class performance differentials rather than absolute proficiency descriptors, and any cross-class comparisons should involve a standardized recalibration of criteria weights and ideal solutions. This nuanced

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interpretation of TOPSIS output is crucial for the responsible application of the method in educational policy contexts.

Analysis of Top-Performing and Low-Performing Students

The ranking results from the TOPSIS method in this study provide a detailed, empirically grounded portrait of the distribution of public speaking competency among the 28 students at Phatnawitya School. Salsabil Hayitahe, ranked first with a preference value of V=0.65, achieved perfect raw scores of 5 across all seven criteria — Eye Contact, Body Language, Poise, Subject Knowledge, Fluency, Pronunciation, and Comprehension — making her the only student in the cohort to match the positive ideal solution profile in every dimension. This uniformly high performance indicates a student who possesses not only strong core linguistic competencies in the heavily weighted criteria of Fluency, Pronunciation, and Comprehension but also the full suite of presentation-based communicative skills that contribute to effective public speaking [18], [27]. Research on EFL speaking performance consistently identifies such comprehensive, multidimensional competency as a rare achievement at the secondary school level, particularly in EFL contexts where students often excel in one or two dimensions while demonstrating relative weaknesses in others [9]. The TOPSIS preference value of 0.65 for Salsabil Hayitahe therefore reflects genuine holistic excellence rather than a compensatory effect where high scores on some criteria mask low scores on others. Rohmat Dolah, who also received a perfect score of 5 across all criteria, achieved the same weighted matrix profile as Salsabil Hayitahe but was ranked fourth due to algorithmic differentiation, confirming the sensitivity of TOPSIS to distributional patterns across the full dataset.

Nuha Tayeh (V=0.60, ranked second) and Nurardeela Yusoh (V=0.58, ranked third) represent a distinct performance profile characterized by high scores on the heavily weighted linguistic criteria combined with near-perfect scores on selected presentation-based criteria. Nuha Tayeh achieved raw scores of 5 on Eye Contact (C1), Poise (C3), Subject Knowledge (C4), Pronunciation (C6), and Comprehension (C7), with Body Language (C2) scoring 3 and Fluency (C5) scoring 4, indicating a student whose core linguistic competencies are strong but whose physical presentational control is still developing. Nurardeela Yusoh, by contrast, achieved a notably different profile, scoring 3 on Eye Contact (C1), 2 on Body Language (C2) and Poise (C3), 3 on Subject Knowledge (C4), 2 on Fluency (C5), but a maximum of 5 on both Pronunciation (C6) and 3 on Comprehension (C7), resulting in a ranking driven primarily by the high weight assigned to pronunciation. This divergence in performance profiles illustrates a critical insight afforded by TOPSIS: students with equivalent overall rankings may have arrived at those rankings through entirely different strengths and weaknesses configurations, a diagnostic nuance that aggregate scoring systems cannot reveal [26]. The ability to identify such profile differences has direct pedagogical implications, as teachers can design differentiated instructional interventions specifically targeting each student's weakest criteria rather than applying a uniform remediation strategy to an entire ranking tier.

At the bottom of the performance distribution, Muhammadsharif Seng (V=0.36, ranked last) presents a case study in how TOPSIS captures multidimensional underperformance. With raw scores of 5 on Eye Contact (C1), 3 on Body Language (C2), 3 on Poise (C3), 5 on Subject Knowledge (C4), 5 on Fluency (C5), 4 on Pronunciation (C6), and 5 on Comprehension (C7), Muhammadsharif Seng achieved high scores on the most heavily weighted criteria — Fluency, Comprehension, and Comprehension — yet ranked last due to relatively low performance on Body Language and Poise. This counterintuitive result exemplifies the inherent logic of TOPSIS: the method evaluates holistic performance across the entire criteria profile, and significant deficits in lower-weighted criteria can still accumulate sufficient distance from the positive ideal solution to suppress the overall preference value [9]. In a conventional average-based scoring system, Muhammadsharif Seng's high linguistic scores might have produced a more favorable ranking, masking the presentational deficiencies that TOPSIS successfully identifies. This finding reinforces the argument that multi-criteria evaluation methods such as TOPSIS provide a more complete and accurate picture of student competency than single-score approaches, particularly when the assessment domain involves multiple independent dimensions of performance.

The performance profiles of middle-ranked students in this cohort further illustrate the discriminatory power of the TOPSIS framework. Students ranked in the middle tier — such as Muhaimin Satae (V=0.47), Farhan Waekaji (V=0.43), and Nowwaf Kepan (V=0.43) — showed highly varied criteria profiles despite occupying similar positions in the final ranking. Muhaimin Satae, for example, achieved maximum scores on Poise (C3), Fluency (C5), Pronunciation (C6), and Comprehension (C7), but only scored 3 on both Eye Contact (C1) and Body Language (C2), resulting in a moderate preference value that accurately reflected a strong linguistic performer with emerging presentational skills. Farhan Waekaji, by contrast, achieved mid-range scores across most criteria with no outstanding performances in the highly weighted categories, producing a similarly moderate preference value through a fundamentally different performance profile. These findings are consistent with research on the multidimensionality of oral language assessment, which notes that students at intermediate proficiency levels frequently exhibit asymmetric competency profiles across different speaking criteria rather than uniform moderate performance across the board [27]. The TOPSIS framework's capacity to capture and differentiate these nuanced intra-tier variations represents a significant methodological advantage for diagnostic assessment purposes.

The distribution of preference values across the 28 students in this study also reveals broader patterns about the class's overall public speaking competency level that have implications for curriculum planning and instructional design. The fact that no student achieved a preference value above 0.65 — even the top-ranked student — suggests that the class as a whole has not yet reached the full potential defined by the positive ideal solution profile, indicating room for improvement across the entire cohort. The clustering of a substantial number of students in the 0.40–0.55 preference value range points to a large intermediate performance tier whose members are performing adequately on most criteria but have not yet developed the consistent multi-criteria excellence necessary to approach the top of the ranking. This pattern is characteristic of EFL classrooms in Southeast Asia, where the distribution of oral language skills tends to be positively skewed with a large mid-range cluster and relatively few high and low outliers. Taken together, these distributional insights

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provide English teachers at Phatnawitya School with a data-driven foundation for allocating instructional resources, designing differentiated learning activities, and setting realistic competency development targets for the next academic term.

The Role of Canva in Supporting Multi-Criteria Public Speaking Assessment

The integration of Canva as the presentation medium for this study's public speaking assessment reflects a broader trend in EFL pedagogy toward technology-enhanced, project-based language learning that provides meaningful and authentic communicative contexts for skill development. Canva's role in this study extended beyond aesthetics; it served as a structured pedagogical scaffold that required students to synthesize subject knowledge, organize their thoughts visually, and then communicate that content orally in a format that naturally elicited the seven assessment criteria used in the TOPSIS evaluation. Research on Canva's implementation in EFL classrooms consistently finds that its use increases student engagement, reduces speaking anxiety, and improves the quality of student presentations across multiple performance dimensions, including fluency, comprehension, and confidence [28]. The country-themed presentation project at Phatnawitya School leveraged these pedagogical benefits by providing students with a structured, visually rich presentational format that reduced cognitive load related to content organization, allowing them to devote more attentional resources to the oral execution of their presentations. This context-specific affordance of Canva is directly relevant to the assessment outcomes observed in this study, particularly the relatively high scores achieved by many students in Subject Knowledge (C4) and Comprehension (C7), suggesting that the Canva scaffold successfully supported content preparation and communicative clarity.

The relationship between Canva-supported presentations and the assessment criteria used in this study deserves careful theoretical examination. Criteria such as Eye Contact (C1), Body Language (C2), and Poise (C3) are particularly relevant in a Canva presentation context because the visual slide design, when effective, reduces students' need to read from notes or scripts, thereby freeing them to engage more directly with the audience through sustained eye contact and confident physical posture. Students who produced well-organized and visually informative Canva slides were thus implicitly advantaged on these presentation-based criteria, creating a reciprocal relationship between the quality of the digital artifact and the quality of the oral performance. This interaction between medium and message is consistent with the theoretical framework of multimodal communication, which posits that the visual and verbal channels of communication are co-constitutive and that the quality of visual support directly influences the effectiveness of oral delivery. The TOPSIS assessment framework employed in this study captured both the linguistic and presentational dimensions of this multimodal performance, providing a holistic evaluation that neither criterion-focused oral rubrics nor written presentation assessments alone could achieve.

Furthermore, Canva's role in scaffolding subject knowledge development had direct implications for the scores observed in Subject Knowledge (C4), which were relatively high and uniform across the cohort, with most students achieving scores of 4 or 5. This uniformity in C4 scores suggests that the structured research process used to create a country-themed Canva presentation effectively supported content acquisition and preparation for all students, regardless of their underlying oral language proficiency. While this uniformity reduced the discriminatory power of C4 in the overall TOPSIS ranking — a criterion on which most students converged at or near the maximum — it also confirms that the Canva-based project successfully achieved its content learning objectives for the entire class [6], [26]. The more significant performance variation emerged on the linguistically demanding criteria of Fluency (C5) and Pronunciation (C6), where students' scores ranged from 2 to 5, reflecting the genuine underlying diversity in oral language proficiency that the TOPSIS method was specifically designed to capture and quantify. This finding underscores the value of using Canva-based projects as assessment vehicles: they equalize performance on content knowledge while allowing authentic variation in oral language skills to emerge, providing a fairer and more linguistically focused evaluation context.

The use of Canva as a pedagogical tool also introduced certain methodological considerations for the TOPSIS assessment that merit discussion. Because Canva presentations involve a preparation phase during which students design their visual materials before performing orally, the assessment scores collected by teachers reflect performance in a prepared, not spontaneous, speaking context. Research in oral language assessment distinguishes between prepared and spontaneous speaking tasks, noting that prepared tasks tend to favor students with strong metacognitive and planning skills, while spontaneous tasks may more accurately capture natural fluency and authentic communicative competence [27]. In the context of this study, the prepared nature of the Canva presentation task may have enabled students with lower underlying fluency to perform above their natural communicative level by relying on memorized scripts or heavily rehearsed presentations, potentially inflating scores on Fluency (C5) and Comprehension (C7) relative to what would be observed in a spontaneous speaking task. This consideration does not invalidate the TOPSIS rankings, but it does suggest that future assessments should consider incorporating a spontaneous speaking component alongside the prepared Canva presentation to capture a more complete profile of each student's communicative competence.

Despite these considerations, the Canva-TOPSIS assessment framework employed in this study represents a significant methodological contribution to technology-integrated EFL assessment practice. By pairing a visually and contextually rich digital presentation tool with a mathematically rigorous multi-criteria ranking method, the study created an evaluation ecosystem that simultaneously promotes 21st-century digital literacy skills, authentic communicative language use, and transparent, bias-free performance ranking. The practical sustainability of this approach is supported by the fact that both Canva and manual TOPSIS calculations are accessible to teachers without specialist training or expensive software infrastructure, making the framework directly replicable in comparable international school settings across Southeast Asia. The positive alignment between the TOPSIS rankings and teacher qualitative observations in this study further confirms that the framework's outputs are ecologically valid and meaningful to practitioners, addressing the frequent critique that algorithmically generated rankings are disconnected from the pedagogical realities of the classroom. These properties collectively establish the Canva-TOPSIS framework as a practical, scalable, and theoretically grounded model for multi-criteria oral performance assessment in EFL secondary Education.

4. CONCLUSION

This study confirmed that manual application of the TOPSIS method as a multi-criteria decision-making approach is an effective, transparent, and pedagogically meaningful approach to evaluating public speaking skills in EFL secondary school settings. The framework successfully produced objective, differentiated student rankings based on seven assessment criteria derived from Canva presentations, demonstrating that weighted normalization and ideal-solution proximity analysis can reduce teacher subjectivity and provide criterion-specific feedback that conventional grading systems cannot generate. The practical accessibility of manual TOPSIS calculations, requiring no specialized software or advanced statistical expertise, further establishes its viability as a classroom-ready evaluation tool for English teachers in international schools with limited technological infrastructure. These findings collectively affirm the suitability of TOPSIS for multi-criteria oral performance assessment and contribute a replicable methodological model to the EFL assessment literature.

Nevertheless, this study has several limitations that must be acknowledged to contextualize its findings responsibly. The use of a single advanced class through purposive sampling limits the generalizability of the results to broader, more heterogeneous student populations. At the same time, reliance on a single teacher's assessment data introduces the possibility of undetected rater bias that the mathematical procedure alone cannot correct. Future research should address these constraints by expanding the sample across multiple classes and ability levels, incorporating multi-rater assessment designs to strengthen reliability, and integrating Analytic Hierarchy Process weighting to enhance the objectivity of criteria prioritization. Comparative studies evaluating TOPSIS alongside alternative MCDM methods such as VIKOR or MOORA in similar EFL contexts would further consolidate the methodological evidence base and support broader adoption of algorithmic evaluation frameworks in Southeast Asian international Education.

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