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An analytic hierarchy process–based student arrangement in post-COVID-19

Liang-Ching Chen[1] and Kuei-Hu Chang[2*]

[1]Department of Foreign Languages, Republic of China Military Academy, Kaohsiung, Taiwan. [2]Department of Management Sciences, Republic of China Military Academy, No. 1, Weiwu Rd., Fengshan Dist., 830, Kaohsiung, Taiwan. *Author for correspondence. E-mail: evenken2002@yahoo.com.tw

ABSTRACT. In the post-COVID-19 era, balancing public health with effective education is essential. Schools have adopted blended learning models combining in-person and distance classes to reduce large gatherings. While distance learning offers flexibility and safety, it poses challenges such as limited supervision, technical barriers, and reduced peer interaction, which can hinder student engagement and performance. Taiwanese elementary schools traditionally use randomization to assign students to classes, promoting fairness but neglecting differentiated learning based on academic performance. To address this, primary education must focus on supporting students with lower academic achievement. This study proposes an analytic hierarchy process (AHP) method to evaluate students' academic performance and guide class arrangements, ensuring a more tailored and effective learning environment. In particular, pupils' midterm test scores at a Taiwanese public elementary school ($N = 25$) were adopted as an empirical case. Results indicated that the AHP method reduced the respective internal academic performance gaps in in-person classes ($N = 12$, $M = 80.33$, SD = 6.52) and distance learning classes ($N = 13$, $M = 93.38$, SD = 2.03). Furthermore, the academic performances of the two types of classes had significant differences ($t = 6.58$, $p < 0.001$). The AHP method effectively selects students with similar academic performance levels into the same learning group, reducing the troubles of students' with different learning levels within the class and improving their overall learning performance. Moreover, the evaluated results of the subjects' relative importance are expected to meet future education trends.

Keywords: Student arrangement issue; post-pandemic; distance teaching; COVID-19; analytic hierarchy process.

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Introduction

As of late 2021, COVID-19 had resulted in over 239 million confirmed cases and 4.8 million deaths worldwide. Public health measures such as city lockdowns, school closures, and restrictions on non-essential activities were proven effective in reducing infections, saving lives, and preventing healthcare systems from being overwhelmed by COVID-19 patients (Chen et a., 2020; Kissler et a., 2020). However, governments cannot sustain the severe economic impact of these preventive measures or endure the escalating public health challenges, including widespread unemployment, rising poverty, and prolonged school closures (Dasgupta et al., 2021). Thus, Joffe (2021) proposed prioritizing the protection of high-risk populations while reopening schools and transitioning to a greener economy—lowering COVID-19 alert levels under specific conditions and gradually resuming normal life. In the context of education, distance learning is widely used in maintaining student learning and academic performance during school shutdowns (Tomasik et al., 2021). While distance learning during school closures has been linked to improved academic outcomes (Clark et al., 2021), it also disrupts the structured environment and support systems of in-person education, leading to significant challenges. The lack of regular supervision, peer engagement, extracurricular activities, and access to guidance counseling increases students' vulnerability to risky behaviors, such as teen pregnancy, substance abuse, and delinquency (Chanchlani et al., 2020; Silverman et al., 2020). These issues are particularly pronounced in underprivileged communities, where reduced access to resources exacerbates lower graduation rates and heightened juvenile crime. In the post-COVID-19 period, it is crucial to balance public health and education as people gradually resume daily life (Joffe, 2021). This paper proposes that schools adopt a dynamic approach by combining in-person and distance learning to reduce on-campus populations. The key challenge is determining how to allocate students effectively between these two modes to monitor and optimize academic performance.

Effectively allocating students to classes is a critical decision. Many schools use the randomization method to ensure fairness—a widely used research design in clinical, experimental, and quasi-experimental studies that equally and randomly distributes participants (Lai et al., 2021; Yu & Koch, 2021). For instance, Waxman et al. (2021) adopted the randomization method to distribute patients to different treatment groups (i.e., inhaled treprostinil and placebo) to verify their proposed therapy method in pulmonary hypertension due to interstitial lung disease. On the other hand, Xu et al. (2021) utilized the randomization method to randomly assign patients to the complete mesocolic excision (CME) group and the D2 dissection group to explore the outcomes of complete mesocolic excision and D2 dissection in patients who underwent laparoscopic colectomy for right colon cancer (RELARC). Educators often prefer the randomization method for assigning students to groups or classes because it ensures equal and unbiased distribution. However, this approach is less effective for student arrangement, as it fails to accommodate differentiated learning based on academic performance levels, which is critical for enhancing overall learning. This issue is particularly pronounced in distance learning during the COVID-19 pandemic, where significant disparities in academic performance can hinder course progress and learning outcomes. Comprehensive evaluation of academic performance must also account for multiple criteria, including subject-specific scores, to provide a complete assessment.

The analytic hierarchy process (AHP) has proven effective for solving complex multi-criteria decision-making (MCDM) challenges, including student arrangement (Oliveira et al., 2012). Introduced by Saaty in 1980, AHP addresses complex social decision-making by systematically breaking down problems into a hierarchical structure and integrating evaluation results, ensuring thorough and comprehensive decision-making (Moretti et al., 2017). Further, it has been widely used in various decision-making applications such as failure mode and effect analysis (Yucesan & Gul, 2021; Chang, 2016), online learning in higher education (Cho & Woo, 2022), reliability allocation (Bai et al., 2022), supplier selection (Ho et al., 2021; Chang et al., 2016; Selvam et al., 2021), coastal water quality assessment (Xiao et al., 2022), the selection of solid waste truck-compactors (Silva & Souza, 2011), and military simulation training systems (Chang et al., 2015). For instance, Gutierrez et al. (2021) developed an innovative AHP-MCDM model combining economic and environmental criteria to evaluate public road transportation vehicles based on alternative engine technologies and combustion features during the COVID-19-induced economic crisis. Their findings identified the most sustainable option, offering valuable guidance for policymakers and companies in strategic decision-making. On the other hand, Yetim et al., (2021) used the AHP-based method to determine how practices and policies used for fighting COVID-19 were prioritized by health care and social groups. In particular, they discovered that the test policy of COVID-19 was regarded as the most important task in both groups. They also found that social welfare programs were considered more important than economic measures for social groups, while health care workers were more concerned with economic measures. The contributions of their research provided evidence-based information for decision-makers in fighting the COVID-19 pandemic.

The traditional randomization method for student allocation aims to promote fairness but fail to consider academic performance disparities, limiting their effectiveness in blended learning environments. These disparities, compounded by challenges like reduced teacher supervision and peer interaction in distance learning, highlight the need for a more tailored approach. This paper addresses this gap by proposing an AHP-based method that incorporates academic performance and expert input to allocate students to in-person or distance learning classes. By minimizing disparities within classes, this approach enhances learning outcomes while balancing public health policies with academic needs. An empirical example using mid-term test scores from a Taiwanese elementary school validates its effectiveness.

The remaining sections are organized as follows: Section 2 is *Materials and Methods*, which explains the proposed approach in detail; Section 3 is *Results*, which includes the results of the randomization method, the proposed approach, and method comparison; Section 4 is *Discussion*, which is the concluding part of this paper.

Methodology

Reducing the daily population at schools may be a good solution for reducing the risks of infection in large-scale clusters and preventing overall school shutdown amid the COVID-19 pandemic. This goal can be achieved by allocating students to in-person and distance learning classes. However, the randomization method does not provide an avenue for differentiated learning that takes into account students' academic performance levels to improve their overall learning. To effectively implement in-person and distance learning classes simultaneously and decrease the daily population at schools, the allocation of students should reach the following two criteria simultaneously:

(i) Distribute students based on their academic performances.

(ii) Integrate experts' comments to evaluate the relative importance of the subjects to meet future education trends.

The AHP method was chosen for its ability to systematically handle complex multi-criteria problems, aligning with the study's goal of evaluating students' academic performance across multiple subjects. By integrating expert opinions through pairwise comparisons, AHP provides a robust framework for assigning relative weights to criteria, ensuring reliability and validity through its consistency ratio. This approach addresses the limitations of the traditional randomization method (Lai et al., 2021; Yu & Koch, 2021), commonly used in Taiwanese public schools, which neither accounts for academic performance differences nor supports differentiated learning. The proposed AHP-based assessment method allocates students based on academic performance and incorporates expert feedback to determine the relative importance of subjects, meeting future education trends. Detailed steps of the approach are illustrated in (Figure 1).

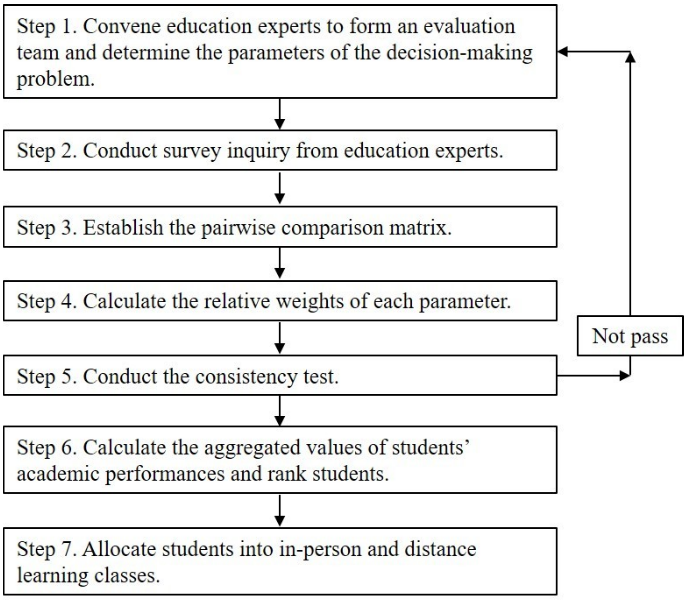

Figure 1. The flowchart of the proposed approach.

Step 1. Convene education experts to form an evaluation team and determine the parameters of the decision-making problem.

This research gathers education experts (i.e., teachers) to form an evaluation team in order to conduct a decision analysis of the discussed public health concern in the context of education. In addition, this study also focuses on evaluating students' academic performances in each subject (i.e., Chinese, Mathematics, Science, Society, and English) to meet the aforementioned criteria.

Step 2. Conduct a survey inquiry from education experts.

Considering that the school focuses on different subjects according to different learning stages, there is also a difference in the relative importance of these subjects. Thus, the assessment approach must incorporate experts' professional comments to determine the relative importance of each subject in order to meet future trends in student learning development and education. In this step, education experts will base on the pairwise comparison scale (Saaty, 1980) in conducting a pairwise comparison of each subject to reflect on their subjective preferences (Table 1). If a decision-making problem includes n parameters, then $\frac{n(n-1)}{2}$ pairwise comparison will be carried out.

Table 1. The pairwise comparison scale (Saaty, 1980).

Relative importance scale	Description
1	Indicate equal importance between two criteria.
3	Indicate moderate importance of one criterion over another.
5	Indicate strong importance.
7	Indicate very strong importance.
9	indicate extreme importance.
2, 4, 6, 8	Intermediate values can be used for compromises between adjacent judgments.

Step 3. Establish the pairwise comparison matrix.

Experts' comments on the pairwise comparison from the questionnaire survey are integrated to construct the pairwise comparison matrix (Equation 1).

$$A = \begin{bmatrix} 1 & a_{12} & \cdots & a_{1n} \\ 1/a_{12} & 1 & \cdots & a_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ 1/a_{1n} & 1/a_{2n} & \cdots & 1 \end{bmatrix} (1)$$

Then, based on (Equation 2), the eigenvalue and eigenvector are computed.

$$A \cdot X = \lambda \cdot X \ (2)$$

where A is the $n \times n$ pairwise comparison matrix; X represents the eigenvector of matrix A; and λ represents the eigenvalue of matrix A.

Step 4. Calculate the relative weights of each parameter.

Once the maximal eigenvalue λ_{max} is obtained, based on (Equation 3), the relative weights (W) of each parameter are calculated.

$$A \cdot W = \lambda_{max} \cdot W, \text{ and } \sum_{i=1}^{n} w_i = 1 \ (3)$$

Step 5. Conduct the consistency test.

In this step, the consistency tests were conducted (i.e., the AHP method's reliability and validity test). The elements of the pairwise comparison matrix were derived from experts' professional comments. Hence, to check whether the pairwise comparison matrix follows the transitivity, consistency tests were conducted via (Equation 4) to calculate the consistency index (CI). Further, (Equation 5) was used to calculate the consistency ratio (CR). If CR $\leq$ 0.1, it indicates that the experts' evaluation results and the relative weights are acceptable.

$$CI = \frac{\lambda_{max} - n}{n-1} \ (4)$$

$$CR = \frac{CI}{RI} \ (5)$$

where λ_{max} is the maximal eigenvalue; n is the dimension of the pairwise comparison matrix; and random index (RI) represents the random index (Table 2).

Table 2. RI table (Saaty, 1980).

n	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
RI	N/A	N/A	0.58	0.90	1.12	1.24	1.32	1.41	1.45	1.49	1.51	1.48	1.56	1.57	1.59

Step 6. Calculate the aggregated values of students' academic performances and rank students.

The aggregated value of students' academic performances is calculated by multiplying the relative weights of the results for the five parameters from Step 4 (Equation 6). Then, students are ranked based on their respective weighted aggregated values of academic performance.

$$\text{aggregated value} = \sum_{i=1}^{5} w_i \cdot (p_i) \ (6)$$

Step 7. Allocate students into in-person and distance learning classes.

Based on the ranking results, the researchers use the median score as the baseline for allocating students. Students whose scores are equal to and higher than the median score will be allocated to distance-learning classes at home, while those whose scores are lower than the median score will be allocated to in-person classes.

Results and discussion

Case Overview

When the simultaneous implementation of in-person and distance learning classes becomes a trend among schools in the post-COVID-19 era, properly arranging students into these two classes becomes crucial. An individual's academic performance often reflects their engagement in schoolwork and their attention from their respective families. Because primary school pupils may be immature and lack autonomous learning, arranging those with low academic achievements into distance learning classes at home will affect or decrease their overall learning performance. Thus, to effectively classify pupils with the same level of academic performance, this paper will discuss the two decision support methods (the randomization method vs. the AHP-based method) in handling student arrangements for distance learning in the post-pandemic era.

In this study, the researchers selected a Taiwanese public elementary school as an empirical case. The participants were divided into two groups: the experts (for AHP-based assessment) and students. In particular, the researchers invited the faculty (*N* = 4) of the Taiwan public elementary school to form an assessment team and evaluate the relative importance of the attributes set in the present study. As the attributes, a class taught by a member of the assessment team was selected. The attributes (i.e., academic subjects) were calculated by the aforementioned two methods to further discuss their pros and cons in conducting student arrangements for distance learning. In the current class, the students' (*N* = 26) average score on midterm tests was initially 86.82 (*SD* = 8.07). Further, it must be noted that no ethical issues were involved in this study.

Results based on the traditional randomization method

The randomization method is a common research design used in many clinical trial studies, which is a less controversial modern method in equally assigning participants (Yu & Koch, 2021). The researchers of this study adopted the randomization method to allocate students based on the students' average scores in all subjects on the mid-term exam. Thus, students were randomly and almost equally allocated to two groups. As shown in (Table 3), there was no significant difference in the academic performances (i.e., scores) of the two groups (t = 0.04, p > 0.05). However, the individual scores differed greatly in both Group A (*N* = 13, *M* = 86.90, *SD* = 9.64) and Group B (*N* = 12, *M* = 86.73, *SD* = 8.33). This finding implies that if the school management adopts the traditional randomization method to allocate students, the following deficiencies will occur:

(1) Although this method assigns students to two classes randomly and equally, it does not consider their academic performance and may cause a large gap in the academic performances of the students in each group;

(2) Randomly arranging students without basing the decision on their academic performances will make it difficult for in-service teachers to monitor and control the curriculum progress due to the large gap in students' academic performance in each class;

(3) As it does not integrate experts' comments in evaluating the relative importance of the subjects to future education trends, the calculation of students' academic performance can only rely on the arithmetic average of all subjects, which considers that all subjects are equally important. However, it is inconsistent with the real-world situation because the subjects emphasized at different educational stages should not be the same.

Table 3. Results of grouping students via the randomization method.

Group	*N*	Mean (M)	Standard Deviation (SD)	*t*	*p*
A	13	86.90	9.64	0.046	0.964
B	12	86.73	8.33		

Results of the proposed AHP-based assessment approach

The AHP method has been widely employed to guide decision-makers in integrating and evaluating multi-criteria decision activities. Therefore, to simultaneously consider all attributes (i.e., the Chinese, Mathematics, Science, Society, English subjects), this paper proposes an AHP-based method for arranging students in the context of education. The results of the proposed approach are described in each step as follows:

Step 1. Convene education experts to form an evaluation team and determine the parameters of the decision-making problem.

The researchers recruited four in-service teachers from a Taiwanese elementary school who have many years of experience in education. Relying on the richness of their teaching experience, all team members unanimously agreed that students' academic performances should be used as the standard for allocating students. Further, during the AHP-based assessment procedure, they considered students' competitiveness on future education trends and provided accurate assessments of the relative importance of the attributes.

After the discussion, the criteria (N = 5) set in this study were the following academic subjects: Chinese, Mathematics, Science, Society, and English. Noteworthily, these subjects were considered suitable for evaluating students' academic performances as they appear on the mid-term and final exams.

Step 2. Conduct a survey inquiry with education experts.

After the experts fully considered the importance of each subject for the students' future competitiveness, the pairwise comparison scale (Saaty, 1980) was used to conduct pairwise comparisons among the subjects. The experts' comments are presented in (Table 4).

Table 4. Results of education experts' comments.

Subject	Experts	Experts' comments				
		Chinese	Mathematics	Science	Society	English
Chinese	Teacher 1	1.00	1.00	3.00	3.00	2.00
	Teacher 2	1.00	5.00	5.00	5.00	3.00
	Teacher 3	1.00	1.00	5.00	5.00	3.00
	Teacher 4	1.00	1.00	7.00	7.00	1.00
Mathematics	Teacher 1	1.00	1.00	5.00	5.00	2.00
	Teacher 2	0.20	1.00	3.00	3.00	3.00
	Teacher 3	1.00	1.00	5.00	5.00	3.00
	Teacher 4	1.00	1.00	9.00	9.00	1.00
Science	Teacher 1	0.33	0.20	1.00	1.00	0.50
	Teacher 2	0.20	0.33	1.00	1.00	0.33
	Teacher 3	0.20	0.20	1.00	1.00	0.33
	Teacher 4	0.14	0.11	1.00	1.00	0.20
Society	Teacher 1	0.33	0.20	1.00	1.00	0.50
	Teacher 2	0.20	0.33	1.00	1.00	0.33
	Teacher 3	0.20	0.20	1.00	1.00	0.33
	Teacher 4	0.14	0.11	1.00	1.00	0.20
English	Teacher 1	0.50	0.50	2.00	2.00	1.00
	Teacher 2	0.33	0.33	3.00	3.00	1.00
	Teacher 3	0.33	0.33	3.00	3.00	1.00
	Teacher 4	1.00	1.00	5.00	5.00	1.00

Step 3. Establish the pairwise comparison matrix.

The researchers used (Equation 1) to establish a pairwise comparison matrix and filled the arithmetical average of experts' evaluation results in the matrix for further computation (Table 5).

Table 5. The establishment of the pairwise comparison matrix.

Subject	Chinese	Mathematics	Science	Society	English
Chinese	1.00	2.00	5.00	5.00	2.25
Mathematics	0.50	1.00	5.50	5.50	2.25
Science	0.20	0.18	1.00	1.00	0.31
Society	0.20	0.18	1.00	1.00	0.31
English	0.44	0.44	3.25	3.25	1.00

Step 4. Calculate the relative weights of each parameter.

(Equation 2) and (Equation 3) were used to compute the pairwise comparison matrix (Table 4), which revealed the maximum of the eigenvalue, λ_{max} was 5.3815, and the relative weights of Chinese, Mathematics, Science, Society, and English subjects were 0.3726, 0.3205, 0.0629, 0.0629, and 0.1812, respectively. Notably, the evaluation team considered that the relative importance between subjects was not equal; the order of each subject's importance levels—from the most important to the least—was Chinese (0.3726), Mathematics (0.3205), English (0.1812), Science (0.0629), and Society (0.0629).

Step 5. Conduct the consistency test.

In verifying the reliability and validity of the relative weights, (Equation 4) and (Equation 5) were employed to calculate the CI and CR values, 0.0954 and 0.0851, respectively. The $CR \leq 0.1$ indicated that the results were acceptable.

Step 6. Calculate the aggregated values of students' academic performances and rank students.

After the relative weights passed the consistency test, the researchers, based on (Equation 6), integrally computed the relative weights and students' scores in the subjects to obtain the aggregated values. Then, the aggregated values were used to rank the students (Table 6).

Table 6. Results of the aggregated values of students' academic performance and their ranks.

Rank	Student	Students' scores in each subject					Aggregated value
		Chinese	Mathematics	Science	Society	English	
1	Student 13	98.44	96.05	97.85	93.20	98.40	97.30
2	Student 8	97.81	95.55	99.20	98.00	90.60	95.88
3	Student 3	93.29	98.36	98.75	86.00	97.60	95.58
4	Student 5	95.01	93.92	96.00	86.00	96.80	94.48
5	Student 17	97.75	91.27	96.85	91.20	92.20	94.20
6	Student 15	95.85	87.97	96.75	92.40	97.60	93.48
7	Student 12	95.99	87.60	94.90	94.80	97.00	93.34
8	Student 10	97.56	86.76	97.10	89.40	95.20	93.13
9	Student 19	95.40	88.54	91.70	93.00	95.20	92.78
10	Student 6	96.51	84.89	98.95	84.20	94.40	91.78
11	Student 16	92.59	86.09	98.60	87.80	95.20	91.06
12	Student 18	94.20	88.57	97.60	77.20	90.60	90.89
13	Student 25	93.81	80.99	95.10	96.80	94.40	90.08
14	Student 20	95.30	77.49	92.60	87.20	93.80	88.64
15	Student 22	95.75	76.26	86.60	82.80	98.40	88.59
16	Student 9	90.46	77.32	96.30	79.20	97.00	87.09
17	Student 21	96.25	66.86	90.35	84.40	94.40	85.38
18	Student 24	86.96	69.52	92.50	75.20	96.20	82.65
19	Student 11	83.44	74.07	85.50	73.20	94.40	81.91
20	Student 7	86.90	73.03	83.10	70.80	84.00	80.68
21	Student 23	91.10	60.26	86.55	64.00	89.80	78.99
22	Student 4	83.06	65.91	78.30	73.40	82.80	76.61
23	Student 14	84.31	59.79	72.95	66.40	83.40	74.45
24	Student 1	71.65	76.02	66.00	24.80	81.00	71.44
25	Student 2	74.30	50.20	64.20	46.80	92.40	67.49

Step 7. Allocate students into in-person and distance learning classes.

The researchers took the median score of the AHP-based results as the benchmark for grouping. Students whose scores were equal to or higher than the median score were allocated to distance learning classes and should accept distance learning at home, while the students whose scores were less than the median score were allocated to in-person classes and should be requested to attend the school.

Table 7 indicates that the respective internal academic performance gaps in the distance learning group (N = 13, M = 93.38, SD = 2.03) and the in-person class group (N = 12, M = 80.33, SD = 6.52) narrowed. Further, the academic performances of the two groups had a significant difference (t = 6.58, $p < 0.001$). In other words, the AHP-based assessment approach for allocating not only considers students' academic performances but also integrates experts' comments to evaluate the relative importance of the subjects in meeting future education trends.

Table 7. Results of the distance and in-person learning classes.

Group	N	Mean (M)	Standard Deviation (SD)	t	p
Distance learning class	13	93.38	2.03	6.58	$p < 0.001$**
In-person class	12	80.33	6.52		

** There is a significant difference in academic performance between the two groups.

This mechanism will reduce the daily population in schools by about 50% because half of the students in each class will stay at home for distance learning. Furthermore, it takes into account students' academic achievements to simultaneously achieve the goal of reducing large-scale gatherings and effectively monitoring students' learning performance.

Discussion and Methods Comparison

The AHP analysis revealed notable variations in the relative importance of academic subjects, as perceived by the expert panel. Chinese and Mathematics emerged as the most critical subjects, with relative weights of

0.3726 and 0.3205, respectively, reflecting their foundational role in students' overall academic development. English, with a weight of 0.1812, was also considered significant, particularly for its relevance in global education trends. Conversely, Science and Society were assigned lower weights (both 0.0629), suggesting a relatively lesser emphasis at this stage of primary education.

These insights underline the need to prioritize core subjects like Chinese and Mathematics when designing curricula or allocating resources in blended learning environments. Furthermore, the AHP results demonstrate the value of integrating expert perspectives to align educational priorities with current and future trends. By leveraging these findings, schools can implement more targeted teaching strategies that address the diverse needs of students, thereby enhancing learning outcomes in both in-person and distance learning settings.

This subsection also compares the traditional randomization method with the proposed AHP-based assessment approach from two perspectives (Table 8). First, the traditional randomization method does not consider students' academic performance in conducting student allocation. When students with low academic achievement are selected for distance learning without timely supervision and guidance from teachers, their academic performance will not improve, making them gradually fall behind and further widening the gap in the academic performance among students. Second, the relative importance of each subject was different from the relative weights of the different subjects. Therefore, when the arithmetic mean is used to simply calculate a student's total score, it will result in a biased evaluation of students' academic performances. Furthermore, the different curriculum hours assigned to each subject in the school also indicated that the relative importance between the subjects was naturally unequal. However, taking the curriculum hours of subjects as benchmarks in determining the relative weights may not be perfect because changes in education policies often fail to keep up with current trends. Therefore, using an AHP-based assessment approach to integrate expert opinions serving at the actual teaching sites into the decision-making process can help reach decisions that reflect the future education trends.

Table 8. Method comparison.

Method	Allocating students based on their academic performance	Integrating experts' comments to evaluate relative weights of the subjects
Traditional randomization method (Yu & Koch, 2021)	No	No
The proposed AHP-based assessment approach	Yes	Yes

Sensitive analysis

This study conducted a sensitivity analysis by applying different combinations of subjective weights to evaluate academic performance. Seven scenarios were designed to observe the effects of weight changes on student rankings across five academic subjects: Chinese, Mathematics, Science, Society, and English. In Scenario 1, the original subjective weights provided by experts were used (Chinese: 0.3726, Mathematics: 0.3205, Science: 0.0629, Society: 0.0629, English: 0.1812). In Scenario 2, equal weights were assigned to all subjects (0.2000 each). For Scenarios 3 to 7, greater importance was individually assigned to one subject while the other subjects were given equal lesser weights. Specifically, in Scenario 3, Chinese was assigned a weight of 0.4000, while the others were 0.1500 each. Similarly, Mathematics, Science, Society, and English were prioritized (i.e., weighted as 0.4000) in Scenarios 4, 5, 6, and 7, respectively, following the same weight distribution pattern.

The ranking outcomes for different weight combinations are presented in (Table 9). The results show that the rankings of top-performing students (e.g., Students 3, 5, and 13) remain stable across all scenarios, indicating that their rankings are less affected by variations in weight combinations. Conversely, the rankings of lower-performing students (e.g., Students 1 and 2) display significant fluctuations, suggesting that their rankings are more sensitive to changes in weights. Scenarios with substantial weight shifts, such as Scenarios 6 and 7, caused more pronounced changes in the rankings of mid-performing students, reflecting the influence of weight adjustments on students near the median. Overall, while the rankings of high-performing students are robust, those of mid- and lower-performing students exhibit moderate to high sensitivity to variations in subject importance, underscoring the need for careful consideration in weight assignment during evaluation.

Table 9. The ranking outcomes based on various weight combinations.

Student	Scenario 1		Scenario 2		Scenario 3		Scenario 4		Scenario 5		Scenario 6		Scenario 7	
	k_j	Rank	k_j	Rank	k_j	Rank	k_j	Rank	k_j	Rank	k_j	Rank	k_j	Rank
Student 1	71.44	24	63.89	25	65.83	25	66.93	24	64.42	25	54.12	25	68.17	25
Student 2	67.49	25	65.58	24	67.76	24	61.74	25	65.24	24	60.89	24	72.29	24
Student 3	95.58	3	94.80	3	94.42	6	95.69	3	95.79	3	92.60	8	95.50	2
Student 4	76.61	22	76.69	22	78.29	22	74.00	21	77.10	22	75.87	21	78.22	22
Student 5	94.48	4	93.55	7	93.91	8	93.64	4	94.16	8	91.66	10	94.36	6
Student 6	91.78	10	91.79	12	92.97	10	90.07	11	93.58	10	89.89	12	92.44	12
Student 7	80.68	20	79.57	20	81.40	21	77.93	20	80.45	20	77.37	20	80.67	21
Student 8	95.88	2	96.23	2	96.63	2	96.06	2	96.97	2	96.67	1	94.82	4
Student 9	87.09	16	88.06	15	88.66	17	85.37	15	90.12	14	85.84	17	90.29	15
Student 10	93.13	8	93.20	8	94.29	7	91.59	9	94.18	7	92.25	9	93.70	7
Student 11	81.91	19	82.12	19	82.45	19	80.11	19	82.97	19	79.89	19	85.19	19
Student 12	93.34	7	94.06	5	94.54	5	92.44	7	94.27	6	94.24	3	94.79	5
Student 13	97.30	1	96.79	1	97.20	1	96.60	1	97.05	1	95.89	2	97.19	1
Student 14	74.45	23	73.37	23	76.11	23	69.98	23	73.27	23	71.63	23	75.88	23
Student 15	93.48	6	94.11	4	94.55	4	92.58	6	94.77	4	93.69	4	94.99	3
Student 16	91.06	11	92.06	11	92.19	12	90.56	10	93.69	9	90.99	11	92.84	10
Student 17	94.20	5	93.85	6	94.83	3	93.21	5	94.60	5	93.19	6	93.44	8
Student 18	90.89	12	89.63	13	90.78	14	89.37	13	91.63	13	86.53	15	89.88	16
Student 19	92.78	9	92.77	9	93.43	9	91.71	8	92.50	12	92.83	7	93.38	9
Student 20	88.64	14	89.28	14	90.78	13	86.33	14	90.11	15	88.76	13	90.41	14
Student 21	85.38	17	86.45	17	88.90	16	81.55	17	87.43	17	85.94	16	88.44	17
Student 22	88.59	15	87.96	16	89.91	15	85.04	16	87.62	16	86.67	14	90.57	13
Student 23	78.99	21	78.34	21	81.53	20	73.82	22	80.39	21	74.76	22	81.21	20
Student 24	82.65	18	84.08	18	84.80	18	80.44	18	86.18	18	81.86	18	87.11	18
Student 25	90.08	13	92.22	10	92.62	11	89.41	12	92.94	11	93.37	5	92.77	11

Conclusion

Schools no longer have to maintain a full-scale shutdown in the post-COVID-19 environment, where vaccination rates increase. However, we still do not want large-scale clusters to cause a new wave of outbreaks. Thus, decreasing the daily population to avoid large-scale school gatherings can be a viable transition mechanism. Deciding who takes in-person classes and distance learning at home by the randomization method may cause doubts, and disputes from students' parents may arise due to concerns that academic performances may drop as a result of distance learning. Furthermore, if the school takes students' academic performances seriously, it will be a high-risk bet to allow students with low academic performance to accept distance learning. Therefore, this paper verifies a low-cost and easy-to-implement decision-making method (i.e., the proposed AHP-based assessment approach) for handling actual education problems during the COVID-19 pandemic. The significant contributions of this paper are as follows: (1) the proposed AHP-based assessment approach can appropriately allocate students based on their academic performances; (2) and integrates experts' comments into the decision-making process and evaluates the relative importance of the subjects in meeting future education trends.

Furthermore, schools can utilize the proposed AHP-based assessment approach in the future to flexibly compute students' mid-term and final academic performance for deciding on the distribution of students to in-person and distance learning classes. Moreover, this mechanism will contribute to the goal of balancing students' academic performances and post-COVID19–related public health policies.

This study focuses on academic performance as the primary criterion for student allocation. However, future research could integrate additional factors, such as socio-economic status, learning preferences, and special educational needs, to create a more holistic and equitable approach. Incorporating these factors could enhance the flexibility and inclusiveness of the proposed AHP-based method, addressing the diverse needs of students in blended learning environments. The study's findings are also subject to limitations, including a small sample size and the specific context of a Taiwanese elementary school, which may affect their generalizability. Future research should expand to larger and more diverse populations to assess the method's applicability across varied educational and cultural settings.

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