INTERNATIONAL JOURNAL OF RESEARCH AND INNOVATION IN SOCIAL SCIENCE (IJRISS)
ISSN No. 2454-6186 | DOI: 10.47772/IJRISS | Volume IX Issue XII December 2025

Users' Preference on Online Learning Platform Using Fuzzy Analytical Hierarchy Process

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DOI: https://doi.org/10.47772/IJRISS.2025.91200310

Received: 06 November 2025; Accepted: 12 November 2025; Published: 17 January 2026

ABSTRACT

Online learning refers to the utilization of online resources for learning activities and the substitution of internet-based virtual sessions. Although various online learning platforms are available, both teachers and students often find it challenging to determine which platform most effectively facilitates learning. This research aims to choose the best online learning platform using the Fuzzy Analytic Hierarchy Process (FAHP) method, which integrates the fuzzy logic and Analytic Hierarchy Process (AHP) approaches. The objective is to weigh and rank alternative platforms based on seven criteria from five decision-makers, who are lecturers from UiTM Cawangan Terengganu experienced in using all three online learning platforms. The findings show that platform compatibility, internet stability, and system quality are the key factors influencing platform preference. Overall, Google Classroom appeared as the most preferred online learning platform (0.7418), followed by Microsoft Teams (0.1922), while UFuture was the least favoured (0.0660). The result will help educators to choose which online learning platform to use during online classes. The survey also provides insights into users' perceptions of online learning.

Keywords: Covid 19, Fuzzy Logic, Fuzzy Analytic Hierarchy Process, Online Learning, Multi-Criteria Decision Making

INTRODUCTION

In 2020, the world faced a major health crisis when the World Health Organization (WHO) declared COVID-19 a global emergency. The pandemic affected nearly every aspect of daily life, including education, travel, business, and social interactions (WHO, 2020). Among all sectors, education was one of the most affected. In just a few weeks, universities had to switch from face-to-face classes to online learning to keep lessons going [1]. However, many institutions were not fully ready for this sudden change. Teachers had to find new ways to make online classes interesting, while students needed to adapt to new tools like Google Classroom and Microsoft Teams [2]. Even though online learning allowed classes to continue, it lacked the personal touch and interaction that happened naturally in physical classrooms [1].

Choosing the most effective online platform became another major challenge. Both educators and students found it difficult to determine which system best supported teaching and learning. Prior studies [3] highlighted that factors such as system quality, user satisfaction, and information quality significantly influence the effectiveness of online platforms. To address this complexity, researchers have increasingly turned to multi-criteria decision-making (MCDM) methods, which allow for systematic comparison of alternatives based on multiple criteria [4].

One of the most widely used MCDM techniques is the Analytic Hierarchy Process (AHP), which helps assign relative importance to evaluation criteria [5]. An advanced version, known as the Fuzzy Analytic Hierarchy Process (FAHP), integrates AHP with fuzzy logic to better handle uncertainty and subjective judgment [6]. Fuzzy logic, developed to mimic human reasoning under ambiguity [7], allows FAHP to capture the nuanced and imprecise nature of real-world decision-making. Consequently, FAHP has been effectively applied across various fields such as banking, mobile technology, and power systems to solve complex decision problems under uncertainty [8].

In the educational context, FAHP has gained recognition for its ability to evaluate teaching strategies, learning systems, and digital platforms more precisely. For instance, [9] used FAHP to assess multiple teaching approaches, demonstrating its capacity to manage uncertainty in pedagogical evaluation. Similarly, [10] argued that traditional AHP may yield inaccuracies due to rigid numerical judgments, whereas FAHP improves reliability by using fuzzy numbers to represent degrees of confidence. Despite its advantages, FAHP also presents challenges, including mathematical complexity and the need for expert interpretation [11]. Studies such as [12] further indicate that, while FAHP enhances decision accuracy, factors like learner characteristics and instructional design still influence outcomes.

Beyond education, FAHP has been successfully implemented in other fields. [13] used FAHP for supplier selection in the Brazilian oil industry, showing its effectiveness in evaluating risks and decision criteria simultaneously. Similarly, [14] applied FAHP in textile research to assess comfort levels, using fuzzy mathematical modelling to capture subjective perceptions. These examples demonstrate that FAHP is a flexible and reliable tool capable of handling complex decision-making challenges across diverse domains.

Despite advancements in online education, few studies have applied FAHP to evaluate and rank online learning platforms in the post-COVID era. This gap highlights the need for a systematic and data-driven approach to determine which platform most effectively supports online learning experiences. Therefore, this study aims to identify and rank three online learning platforms which are UFuture, Google Meet, and Google Classroom based on seven criteria which are platform compatibility, system quality, internet stability, operational convenience, teaching resources, interaction component and ability to organize and categorize content using the FAHP method. The use of FAHP is novel in this context, as it effectively handles uncertainty and subjectivity in evaluating online learning, leading to more informed and reliable platform selection in post-pandemic education.

METHODOLOGY

Step 1: Problem Identification and Criteria Selection

The primary objective of this study is to determine the most suitable online learning platform through a systematic evaluation process. In this study, three platform alternatives are identified, and seven specific criteria are established to assess and compare their performance and effectiveness.

Step 1: List of Alternative and Criteria

TABLE 1 List of Alternative and Criteria

ALT	Alternative
A1	Google Classroom
A2	Microsoft Teams
A3	UFuture
CRI	**Criteria**
C1	Platform compatibility
C2	Internet Stability
C3	System quality
C4	Operational convenience
C5	Teaching Resources
C6	Interaction Component
C7	Ability to organize and categorize content

Step 2: Data Collection

This study involved five decision-makers who were carefully selected based on their expertise and experience in online teaching and learning. All of them are lecturers from UiTM Cawangan Terengganu who have actively used the three online learning platforms being evaluated. Their familiarity with these platforms ensured informed and reliable assessments. The evaluation was based on seven criteria and three platform alternatives. A questionnaire was designed according to these criteria and alternatives, where decision makers rated each criterion on a scale from one to nine to indicate its level of importance. Before answering, the decision makers were briefed on the meaning of each criterion to ensure their understanding and to support accurate and consistent judgments.

Step3: Data Analysis

The data collected from the decision-makers were analysed using the Fuzzy Analytic Hierarchy Process (FAHP) method implemented in Microsoft Excel. The procedure for applying the FAHP consists of the following steps:

i) Develop crisp pairwise comparison matrix.

The data from the questionnaire are transferred to pairwise comparison matrix.

$$\widetilde{A} = \begin{bmatrix} \tilde{p}_{11} & \cdots & \tilde{p}_{1n} \\ \vdots & \ddots & \vdots \\ \tilde{p}_{n1} & \cdots & \tilde{p}_{nn} \end{bmatrix}$$

ii) Check consistency ratio, CR

In deciding on the weight to assign to each criterion, the consistency test acts as a validation test. The formula below was proposed by Saaty (1980) for a consistency ratio (CR) using both the consistency index (CI) and the random index (RI):

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

$$CR = \frac{CI}{RI}$$

$\lambda_{\max}$ = the largest eigenvalue of the comparison matrix

n = number of criteria

RI = the random index generated by Saaty

iii) Developing an Aggregated Fuzzy comparison matrix.

Developing a fuzzy pairwise comparison matrix by converting the crisp pairwise comparison matrix into fuzzy numbers. The range of linguistics is established first. The TFN scale, which ranges from one to nine, is utilized.

TABLE 2: Linguistic Terms with Triangular Fuzzy Numbers

Linguistic Terms	Scale	Fuzzy Scale	Fuzzy reciprocal Scale
Equal Important	1	(1,1,1)	(1,1,1)
Intermediate Preference	2	(1,2,3)	$(\frac{1}{3},\frac{1}{2},1)$
Moderate Importance	3	(2,3,4)	$(\frac{1}{4},\frac{1}{3},\frac{1}{2})$
Intermediate Preference	4	(3,4,5)	$(\frac{1}{5},\frac{1}{4},\frac{1}{3})$
Strongly More Important	5	(4,5,6)	$(\frac{1}{6},\frac{1}{5},\frac{1}{4})$
Intermediate Preference	6	(5,6,7)	$(\frac{1}{7},\frac{1}{6},\frac{1}{5})$
Very Strong Importance	7	(6,7,8)	$(\frac{1}{8},\frac{1}{7},\frac{1}{6})$
Intermediate Preference	8	(7,8,9)	$(\frac{1}{9},\frac{1}{8},\frac{1}{7})$
Extremely Importance	9	(8,9,9)	$(\frac{1}{9},\frac{1}{9},\frac{1}{8})$

When there are many decision-makers, the preferences of each decision-maker $\tilde{p}_{ij}^{k}$, are averaged, resulting in the calculation of $\tilde{p}_{ij}^{k}$, as described in equation below.

$$d_{ij} = \frac{\sum_{k=1}^{K} p_{ij}^{k}}{K}$$

iv) Define Fuzzy Geometric Mean

$$\tilde{r}_i = (\tilde{a}_{i1} \times \tilde{a}_{i2} \times \dots \times \tilde{a}_{in})^{\frac{1}{n}}$$

v) Calculate the weight of fuzzy of each dimension

$$\widetilde{w}_i = \tilde{r}_i \times (\tilde{r}_i + \tilde{r}_i + \cdots + \tilde{r}_i)^{-1}$$

vi) Defuzzification and normalization

Since, the pairwise comparison matrix are fuzzy triangular numbers, they are defuzzied using the centroid method as shown below to obtain the non-fuzzy value, M. The resulting values are then normalized to determine the final weights.

$$M_i = \frac{l_{wi} + m_{wi} + u_{wi}}{3}$$

$$N_i = \frac{M_i}{\sum_{i=1}^{n} M_i}$$

viii) Decision making and final rating

The final scores of the alternatives were calculated using the formula below:

$$S_j = \sum_{i=1}^{7} \widetilde{w}_i \cdot N_{ij}$$

The ranking of the alternative platforms was then determined based on the highest value, with the alternative having the highest score identified as the best platform.

RESULT

The first step of FAHP is to develop crisp pairwise comparison matrix for consistency ratio check for each decision makers.

TABLE 3: Pair Wise Comparison of Decision Maker 1

	C1	C2	C3	C4	C5	C6	C7
C1	1	3	3	3	3	3	3
C2	1/3	1	2	2	2	2	2
C3	1/3	1/2	1	3	4	3	4
C4	1/3	1/2	1/3	1	4	3	2
C5	1/3	1/2	1/4	1/4	1	2	2
C6	1/3	1/2	1/3	1/3	1/2	1	2
C7	1/3	1/2	1/4	1/2	1/2	1/2	1

Based on Table 3, the CR score for decision maker 1 is 0.092 which is less than 0.1. The result element estimates

ISSN No. 2454-6186 | DOI: 10.47772/IJRISS | Volume IX Issue XII December 2025

are acceptable if CR is less than 0.1. All five decision makes have CR scores less than 0.1

The crisp pairwise comparison matrices for the alternative platforms and seven criteria are converted into fuzzy numbers and then averaged across the five decision-makers.

TABLE 4: Aggregated Fuzzy Comparison Matrix (C1)

	A1			A2			A3		
A1	1	1	1	6.6	7.6	8.2	6	7	7.8
A2	1/8	1/7	1/6	1	1	1	5.4	6.2	6.8
A3	1/8	1/7	1/6	1/3	1/3	1/3	1	1	1

Table 4 presents the aggregated fuzzy comparison matrix of the alternative platforms, compiled from the judgments of five decision-makers, for the criteria of platform compatibility (C1). Then the fuzzy geometric mean is calculated as follows:

$$\tilde{r}_i = \left[(1 \times 6.6 \times 6)^{\frac{1}{3}}, (1 \times 7.6 \times 7)^{\frac{1}{3}}, (1 \times 8.2 \times 7.8)^{\frac{1}{3}}\right]$$

$$= [3.4085, 3.7610, 3.9992]$$

TABLE 5: Fuzzy Geometric Mean (C1)

$\tilde{r}_i$			
A1	3.4085	3.7610	3.9992
A2	0.8772	0.9494	1.0326
A3	0.3403	0.3598	0.3888
Total	4.6260	5.0701	5.4205
Power (– 1)	0.2162	0.1972	0.1845
INCR	0.1845	0.1972	0.2162

Then, the final value of relative important for alternative platform for C1 is calculated as follows:

$$\widetilde{w}_i = [3.4085 \times 0.1845, 3.7610 \times 0.1972, 3.9992 \times 0.2162]$$

$$= [0.6288, 0.7418, 0.8645]$$

TABLE 6: Fuzzy Weight of Alternative Platform (C1)

	$\widetilde{w}_i$		
Google Classroom	0.6288	0.7418	0.8645
Microsoft Teams	0.1618	0.1872	0.2232
Ufuture	0.0628	0.0710	0.0840

Since $\widetilde{w}_i$ are still fuzzy triangular numbers, defuzzification is required. The final weights of the criteria and the three alternative platforms are shown in Table 7.

$$M_i = \frac{0.6288 + 0.7418 + 0.8645}{3} = 0.7450$$

TABLE 7: Final Weight of Alternative Platform (C1)

	M_i	N_i
A1	0.7450	0.7388
A2	0.1908	0.1892
A3	0.0726	0.0720

ISSN No. 2454-6186 | DOI: 10.47772/IJRISS | Volume IX Issue XII December 2025

TABLE 8: Non-Fuzzy and Normalized Relative Weights of Alternative with Respect to Criteria.

	Weight (N_i)	A1	A2	A3
C1	0.2981	0.7388	0.1892	0.0720
C2	0.1683	0.7400	0.1891	0.0710
C3	0.1903	0.7459	0.2031	0.0509
C4	0.1282	0.7523	0.1774	0.0703
C5	0.0783	0.7252	0.2038	0.0709
C6	0.0731	0.7342	0.1986	0.0672
C7	0.0637	0.7566	0.1897	0.0537
$S_j = \sum_{i=1}^{7} \widetilde{w}_i \cdot N_{ij}$		0.7418	0.1922	0.0660

TABLE 9: Result For Weight and Rank for Each Alternative

Alternative	Weight	Rank
Google Classroom (A1)	0.7418	1
Microsoft Teams (A2)	0.1922	2
UFuture (A3)	0.0660	3

The results of multiplying the weight of each alternative by the weight of each criterion from Table 8, as well as the ranking of each alternative, were displayed in Table 9. Google Classroom shows the highest value of weight which is 0.7418 followed by Microsoft Teams (0.1922) and UFuture (0.0.660). This indicates that Google Classroom is most likely to be choose by the lecturers of UiTM Cawangan Terengganu during online classes.

DISCUSSION

Based on Table 8, among the seven criteria, platform compatibility (C1) had the greatest influence on the selection of online learning platforms. This aligns with previous studies [2] showing that accessibility across multiple devices is a key factor of user satisfaction and learning management system (LMS) adoption. The next most influential criteria were system quality (C3) and internet stability (C2). Strong system quality reflects a user-friendly interface that enhances the overall learning experience while high internet stability ensures smooth operation and uninterrupted learning sessions. Table 10 presents a comparison of the top three criteria evaluated across the three online learning platforms in this study.

TABLE 10: Comparison Of Online Learning Platform (For C1 To C3)

	A1	A2	A3
C1	Highly compatible with mobile/desktop apps	Moderate compatible with mobile/desktop	Browser-based access makes it usable on all devices
C2	Simple interface but limited features	Advanced interface, users need prior knowledge to use it effectively.	Interface is less intuitive because of institution-specific terminology
C3	Requires moderate to high internet for smooth operation	High internet demand; prone to lag under weak connectivity	Being entirely web-based, may experience slower performance

Google Classroom is a widely used LMS that allows lecturers to communicate with students, create assignments, and share materials in a centralized environment. Its main strengths lie in its simplicity, accessibility, and compatibility across multiple devices. However, it has limited system functionality, such as the absence of a search feature and restricted options for organizing teaching content, which can reduce efficiency when handling large amounts of material.

Microsoft Teams ranked second and serves as an integrated digital hub for communication, collaboration, and content sharing. It supports advanced features such as video conferencing, discussion boards, and file management, which enhance interaction and teamwork. Despite these strengths, its performance depends heavily on internet stability, which may cause lag or slow operation in areas with poor connectivity.

UFuture, UiTM's in-house platform launched in 2019, was designed to enhance accessibility, flexibility, and teaching quality. It is browser-based, compatible with various devices, and can operate efficiently under low internet bandwidth. The platform allows lecturers to organize materials by topic or week and facilitates interaction through tools such as iDiscuss. However, despite its strong institutional integration and functional features, UFuture is less preferred than Google Classroom, likely due to students' unfamiliarity with the platform and its use of organization-specific terminology, which can reduce overall usability.

CONCLUSION

In summary, the analytical results show that Google Classroom is the most preferred online learning platform, as indicated by its highest weight value assigned by UiTM Cawangan Terengganu lecturers, while UFuture received the lowest weight, making it the least favoured option. The results suggest that factors such as platform compatibility, internet stability and system quality play key roles in determining platform preference.

This study demonstrates that the Fuzzy Analytic Hierarchy Process (FAHP) provides a systematic and data-driven approach for evaluating and ranking online learning platforms based on multiple criteria. The findings offer practical insights for educators and institutions in selecting effective platforms that enhance teaching efficiency and student engagement, thereby improving the overall quality of online education.

However, the study's scope is limited by its small sample size of five decision-makers and its context-specific focus on UiTM Cawangan Terengganu, which may influence the generalizability of the results. Future research could expand the sample to include lecturers from various institutions, assess additional platforms, and incorporate student performance or satisfaction data to obtain a more comprehensive evaluation of online learning effectiveness.

ACKNOWLEDGMENT

There is no funding to this article.

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