Analysis of Learning Management Systems Selection using Fuzzy COPRAS

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ABSTRACT
Schools face the problem of the continuity of the teaching and learning process in the classroom when the COVID-19 pandemic occurs. One way to address this issue and continue the school's teaching and learning process is through learning management systems (LMS). There is much demand for online LMS. The LMS available usually offers similar features, and it is hard for users to choose which is appropriate. This research aims to get an overview of using LMS in schools from the teachers' perspective as users. The critical criteria for analyzing LMS are learning skills, communication within LMS, and ease of use tools. This paper aims to systematically review the current LMS, the problem with existing LMS, and the potential solutions that might help. Four learning management systems are chosen: Edmodo, Moodle, Google Classroom, and Microsoft Teams, among the numerous learning management systems in the market. The findings from this review are exciting and can be used to help users such as high schools, universities/colleges, and students select their LMS.

Keywords: *Learning Management Systems, E-learning, Learning-teaching Process, Mobile Learning, Human-computer Interaction.*

1. INTRODUCTION

Numerous changes in how people studied, worked, and interacted with one another were brought on by the COVID-19 pandemic in 2020 [1]. To stop the virus from spreading, educational institutions must transition from traditional face-to-face to online teaching and learning [2]. The transition to online education affects staff, students' mental health, and other lifestyle changes [3].

Students found it challenging to remain motivated and focused on the material of the online teaching process after spending several hours in front of a computer [4]. Some students considered taking leaves of absence or dropping out due to a lack of enthusiasm and unmet expectations regarding school life. Students also only sometimes give responses to teachers and pay attention in class. Teachers face challenges keeping students engaged in the teaching and learning process [5]. Online learning is a challenge for the teacher and student.

Online learning of delivery has certain limitations. After the epidemic began, teachers were compelled to transition quickly to online classes but had trouble re-creating the in-person learning environment [6]. Therefore, the teacher is a crucial figure who significantly impacts students' behaviour during online learning. The attitude of the teachers affects how well students accept e-learning methods [7].

Learning Management Systems (LMSs) are software applications designed to facilitate the administration of educational courses or training programs to support online learning [8]. Academic institutions now frequently run their own LMS and offer a variety of innovative online learning capabilities for a wide range of students. According to Yakubu [9], an LMS is a web-based system with a broad selection of educational and course administration capabilities. Group chats, discussions, document sharing, assignment submission, quizzes, grading, and course evaluations can all be facilitated by LMS using these educational technologies [10]. LMS also has the potential to serve students from various backgrounds, including those related to culture, age, or gender.

Prior research has concentrated on finding different LMS learning elements potentially affecting students' learning results. However, the results of earlier studies were debatable due to the students' variable learning outcomes. Lack of a profound grasp of students' learning

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preferences, needs, and varied backgrounds may be one factor. When implementing LMS in educational environments that will meet the various learning demands of the students, it is necessary to analyze and understand users' preferences because an LMS's primary function is to allow self-regulated learning [10].

Since there are more platforms that LMS can operate on, such as laptops, phones, and tablets, which can help students more conveniently, have high motivation, and be more interested while studying. For example, teachers keep students' attention in the teaching process. Sometimes pupils wish to ask the teacher to explain the issue again but often do not take that move.

Therefore, by considering three crucial independent variables are learning skills, communication within LMS, and ease of use tools. This study intends to investigate critical elements influencing users' preferences for using LMS and get a more profound knowledge of how to enhance learning outcomes using LMS. The findings of this study will help teachers successfully integrate innovative learning in the classroom.

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2. METHODOLOGY

Multi-attribute decision-making (MADM) is selecting preferences by comparing a limited number of predetermined alternatives under multiple, frequently competing attributes. Implicit or explicit trade-offs are also considered in this process [11]. A MADM problem generally contains a limited number of alternatives, a certain number of attributes, weights or degrees of importance of the attributes, and performance measures of the alternatives concerning the attributes [12]. The best option to rank all alternatives is a solution to the issue. The MADM methods used mainly include fuzzy synthetic evaluation—FSE [13], analytical hierarchy process—AHP [14], complex proportional assessment—COPRAS [15], a technique for order of preference by similarity to an ideal solution—TOPSIS [16], graph theory and matrix approach—GTMA [17], multi-objective optimization by ratio analysis—MOORA [18], and many more.

By accounting for uncertainty, fuzzy logic may handle issues without clear boundaries and precise values by accounting for uncertainty. The fuzzy set is a powerful mathematical tool for handling current uncertainty in decision-making [19]. The generic version of a crisp set is a fuzzy set. A fuzzy number falls within the range of closed numbers between 0 and 1, where 1 denotes full membership, and 0 denotes non-membership. Fuzzy logic may handle issues without clear boundaries and precise values by accounting for uncertainty [20]. FMADM was developed by triangular fuzzy number (TFN), linguistic terms, aggregation and averaging, defuzzification, formation of performance rating matrix, weighted normalized performance rating matrix, beneficiary and non-beneficiary, and fitness degree.

Triangular fuzzy numbers (TFNs). TFNs are easy to compute and beneficial in fostering representation and information processing in a fuzzy environment, making them frequently convenient to work with.

A function of fuzzy number $F = \{c, \mu_F | c \in R:\}$, with ‘$c$’ is any real number, $\mu_F(c)$ is continuous membership mapping function $\mu_F(c): R \to [0,1]$.

TFNs are most widely used to narrate experts’ judgment with $T = (t_1, t_2, t_3)$. The parameter (t_1, t_2, t_3) may contain smallest, intermediate, and largest values. The memberships’ function be defined as follows (see figure 1):

$$\mu\left(\frac{c}{T}\right) = \quad \{\, 0, \quad c < t_1 \; (c - t_1)/(t_2 - t_1), \quad t_1 \le c \le t_2 \; \frac{(c - t_1)}{(t_2 - t_1)}, \quad t_1 \le c \le t_2 \quad 0, \quad c \ge t_3 \tag{1}$$

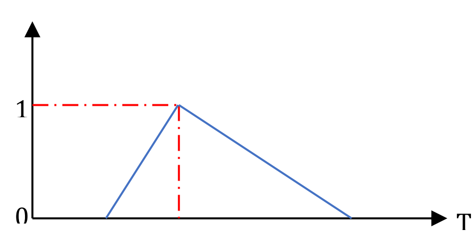

Figure 1. Membeship function of TFNs T = (t_1, t_2, t_3)

Linguistic Terms. A variable that accepts natural language terms as its value is referred to as a linguistic term in Fuzzy Set Theory (FST). On a ten-point fuzzy scale, the weights of the selection indices and the performance ratings of e-learning websites are assessed in linguistic terms. The relevant TFNs for these linguistic phrases are then created.

Aggregation and averaging of TFNs. The TFNs can then be aggregated and averaged using a variety of operators, including mean, median, min, max, average, and mixed operators.

Defuzzification. Defuzzification is a mathematical technique for changing a fuzzy set into a crisp score. It is crucial because fuzzy models must somehow mathematically merge the fuzzy sets produced by fuzzy inference in fuzzy rules to produce a single number as their output.

Formation of performance rating matrix. The performance rating matrix shows how each alternative website performed relative to each selection index, as follows:

$$R = [r_{11} r_{12} \cdots r_{1m} \vdots \ddots \vdots \; r_{q1} r_{q2} \cdots r_{qm}] \qquad (2)$$

Normalized performance rating matrix. Normalization is obtaining each element's dimensionless value in a matrix for straightforward comparison. To ensure consistent convergence of weights and biases, the normalization fits the values of all inputs into the same range of values on a predetermined scale.

Weighted normalized performance rating matrix. Each member of the normalized performance rating matrix multiplies the weight of each selection index to create the weighted normalized performance rating matrix.

The weight of selection indices and the performance ratings of each LMS for each selection index based on the experts' judgment, are determined using:

$$W_i = \left(\frac{1}{n}\right)(W_{i1} \oplus W_{i2} \oplus \dots \dots \oplus W_{in}) = \frac{1}{n}\sum_{j=1}^{n} W_{ij}$$

and

$$R_{ki} = \left(\frac{1}{n}\right)(R_{ki1} \oplus R_{ki2} \oplus \dots \dots \oplus R_{kin}) = \frac{1}{n}\sum_{j=1}^{n} R_{kij}$$

where:

eight = $W_{ij}(i = 1, 2, \dots, m; j = 1, 2, \dots, n)$

performance rating = $R_{kij}(k = 1, 2, \dots, q; i = 1, 2, \dots, m;\ j = 1, 2, \dots, n)$

Averaging and aggregation of weight and performance rating using formula addition ($\oplus$) and ($\ominus$):

$$T_1 \oplus T_2 = (u_1 + u_2, v_1 + v_2, w_1 + w_2)$$

$$T_1 \ominus T_2 = \left(\frac{u_1}{u_2}, \frac{v_1}{v_2}, w_1/w_2\right)$$

Beneficiary and non-beneficiary value. These are the results of algebraically adding the weighted normalized values for each type of selection indices. These metrics demonstrate how well an alternative achieves the desired outcome.

$$Q_i = W_i + \frac{\sum_{j=1}^{n} \quad W_{ij}}{R_{ki}\sum_{j=1}^{n} \quad \frac{1}{R_{ij}}}$$

Fitness Degree. Fitness Degree is the ratio between the database's maximal relative significance level and an alternative's relative significance level value. The relative significant level shows each alternative LMS's level of satisfaction.

$$N_i = \frac{Q_i}{Q_{max}} 100\%$$

3. DATA ANALYSIS

The demographic data of the teachers who participated in this study are shown in Table 1 below. Regarding age, 26-35 years old is 41 teachers (27.7%), 36-45 years old is 82 teachers (55.4%), and 46-55 years old is 25 teachers (16.9%). Concerning the gender group, 50% of pupils were men and women.

Teachers were questioned about how long they had been using the LMS as well as if they had received any prior training in order to see whether experience or instruction before use affected their behavioral intention to utilize the system. A total of 102 teachers (67.1%) reported using the LMS for less than a year, 46 teachers (30.3%) reported using it for more than a year, and four teachers (2.6%) never used LMS. According to this, the bulk of the teachers were inexperienced LMS users. Additionally, 67.6% of the teachers received no instruction before using the system, whereas the remaining 32.4% received training. For demographic characteristics of the respondent, see **Table 1.**

A quantitative research model was used with the questionnaires as a data-gathering method. Making an unambiguously defined software specification is important for quality software development. The features and functions of the software are based on this specification. The factors and criteria for evaluating LMS platforms taken from some references and in this section are presented in **Table 2**.

Table 1. The demographic of the respondents

Demographic Characteristic		Freq	%
Age	26 – 35	41	27.7
	36 – 45	82	55.4
	46 – 55	25	16.9
gender	Male	76	50
	Female	76	50
Length of LMS usage	Not use	4	2.6
	Under 1 year	102	67.1
	Over 1 year	46	46
Training before use of the LMS	Prior training	46	30.3
	No training	106	69.7

Table 2. Criteria Activities for the LMS Platform

	Criteria
Learning Skill tools	L1: Lectures video
	L2: Availability of learning material
	L3: Assignments, exercises, and evaluations
	L4: Online whiteboard
Communication	C1: Chat
	C2: Forum
Productivity tools	P1: need administrator
	P2: need application installation
	P3: can access from mobile handset
	P4: Simple navigation
	P5: Private storage

The importance weights of evaluation criteria and the ratings of alternatives are considered linguistic terms to assess risk under a fuzzy environment. Linguistic values for the importance weight of each criterion are shown in **Table 3.** Weighting the criteria and decision-makers is an essential part of the MDAM process. Decision-makers are assigned eights to reflect their importance or reliability in solving the problem.

Table 3. Linguistic scale for evaluation

Linguistic variables	TFNs
Extremely High (EH)	(9, 10, 10)
Very very High (VVH)	(8, 9, 10)
Very High (VH)	(7, 8, 9)
High (H)	(6, 7, 8)
Above Average (AA)	(5, 6, 7)
Average (A)	(4, 5, 6)
Below Average (BA)	(3, 4, 5)
Low (L)	(2, 3, 4)
Very Low (VL)	(1, 2, 3)
Very very Low (VVL)	(1, 2, 2)
Extremely Low (EL)	(1, 1, 2)

Regarding determining the fuzzy weight of each criterion, linguistic variables are converted into TFNs, as shown in **Table 4.**

Table 4. Fuzzy weight criteria

Criteria	Linguistic term	Fuzzy weight	Crisp weight
L1	VVH	(8, 9, 10)	9
L2	A	(4, 5, 6)	5
L3	VL	(1, 2, 3)	2
L4	VVH	(8, 9, 10)	9
C1	EH	(9, 10, 10)	10
C2	H	(6, 7, 8)	7
P1	VH	(7, 8, 9)	8
P2	L	(2, 3, 4)	3
P3	BA	(3, 4, 5)	4
P4	AA	(5, 6, 7)	6
P5	VVH	(8, 9, 10)	9

Next, linguistic variables shown in **Table 3** were used to create a fuzzy evaluation matrix by decision-makers. It is produced by contrasting eight potential dangers according to five criteria. In **Table 5**, the fuzzy decision matrix is displayed. After making the fuzzy decision matrix, transforms the fuzzy values into crisp values.

The decision matrix created in **Table 5** needs to be normalized using the fuzzy COPRAS method. The weights of the criterion are then multiplied by the normalized decision matrix, as shown in T**able 6**, to determine the weighted decision matrix for the current choices.

Table 5. Fuzzy decision matrix

	LMS-1	LMS-2	LMS-3	LMS-4
L1	8.2	7.6	8.53	8.87
L2	8.2	8.2	8.87	8.4
L3	7.4	8.4	8.53	8.0
L4	8.2	8.13	8.2	8.87
C1	8.4	7.8	8.6	8.93
C2	7.8	7.8	8.73	8.6
P1	7.4	7.4	8.73	8.73
P2	6.8	7.2	8.33	8.2
P3	7.4	7.6	8.2	8.33
P4	8.53	8.4	8	8.53
P5	8.4	7.6	7.6	8.87

Then for four alternatives weight of each alternative is calculated. L1, L2, L3, and L4 are learning skills tools, C1 and C2 are communication within LMS, and P1, P2, P3, P4 and P5 are productivity tools. To validate the methodology, the problem was addressed by selecting and ranking four learning management systems based on eleven selection indices available in the open literature. These rankings were obtained using fuzzy COPRAS in **Table 6**.

Table 6. Fuzzy COPRAS of LMS ranking

Learning Management System	Fitness Degree	Rank
LMS-1	91.89	4
LMS-2	92.56	3
LMS-3	98.64	2
LMS-4	100.00	1

4. RESULTS AND DISCUSSION

Researchers and practitioners in e-learning assessment have recently become interested in multi-attribute decision-making systems. The system quality construct has the second-strongest impact on the students' behavioral intention to utilize the LMS. This study demonstrates that system quality has a positive and substantial association with students' behavioral choice to utilize the LMS. The teacher plays an essential role in the students' usage of the LMS. The teachers' effectiveness has a favorable and significant impact on the students' behavioral intention to use the LMS. The effectiveness of teachers in using LMS depends on how teachers can understand the use of LMS and use LMS effectively and efficiently.

This paper uses Fuzzy COPRAS to evaluate, rank, and choose among four learning management system websites using eleven selection indices (see **Table 2**). Microsoft Teams, a learning management system, has the fitness degree value 100, according to **Table 5**. Google Classroom was ranked at-2 (98.64) and the third is Edmodo (92.56). The Moodle, which had the lowest significance value (91.89), was rated in fourth-to-last place. Pere

The fuzzy COPRAS approach can be successfully used to evaluate, rank, and choose the best learning management system. This method can also be expanded to address other research challenges of a similar nature that can be treated as multi-attribute decision-making problems. Utilizing the fuzzy COPRAS methodology to obtain a thorough rating will assist users in making an informed choice. The fuzzy COPRAS method can offer practitioners and researchers a straightforward, clear, and reliable methodology. It is more acceptable than other MADM approaches for practitioners and researchers due to the clarity of its mathematical formulations and lack of complexity.

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