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RESEARCH ARTICLE

A Hybrid MCDM Approach for Evaluating Web-Based E-Learning Platforms

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ABSTRACT The outbreak of COVID-19 has promoted distance learning and rapidly increased the usage of online learning platforms. As a result, more and more IT companies are competing to offer high-quality Web-based E-Learning Platforms (WELPs). However, the problem facing educational institutions is how to evaluate the quality of WELPs to choose the one that best fulfills their needs. In order to select the most appropriate WELP among different alternatives, many evaluation criteria must be considered by the Decision Maker (DM). Hence, evaluating WELPs is a complex Multi-Criteria Decision Making (MCDM) problem that needs to be addressed efficiently. In literature, we have noticed that MCDM methods are rarely used for evaluating WELPs. In addition, traditional MCDM methods suffer from additive complexity and inconsistency due to the numerous pairwise comparisons of criteria. In contrast, Hybrid MCDM (HMCDM is a promising and more efficient decision-support tool. In this paper, we propose a HMCDM approach for evaluating and ranking WELPs which is more efficient and more reliable than traditional approaches. The proposed approach incorporates different techniques (i.e., BWM, SAW, and Delphi) and comprises the following three phases: 1) a Hierarchical Structure Quality Model (HSQM) is defined in which the evaluation criteria are identified; 2) a Criteria Preference Structure (CPS) is developed where the criteria identified in HSQM are weighted using the pairwise comparison Best-Worst Method (BWM); 3) the performance of alternative WELPs w.r.t criteria is estimated and integrated with the CPS using the Simple Additive Weighting (SAW) method to determine their ranking. The widely used consensus method, Delphi, has been utilized in phases 2 and 3 to estimate the relative preferences of the criteria and the scores of alternatives over these criteria. The proposed approach has been validated and compared to the widely accepted MCDM method, Analytical Hierarchy Process (AHP). The results revealed that the proposed approach surpasses AHP.

INDEX TERMS E-learning, online learning, web-based e-learning, multi-criteria decision-making, best worst method, simple additive weighting, Delphi, analytical hierarchy process.

GLOSSARY

Acronym	Full Name
WELP	Web-based E-Learning Platform.
COVID-19	Coronavirus Disease 2019.
MCDM	Multi-Criteria Decision Making.
HMCDM	Hybrid Multi-Criteria Decision Making.
DM	Decision Maker.
TOPSIS	Technique for Order of Preference by Similarity to Ideal Solution.
MOORA	Objective Optimization by Ratio Analysis.
SAW	Simple Additive Method.
AHP	Analytic Hierarchy Process.
BWM	Best-Worst Method.
ARAS	Additive Ratio Assessment.
WASPAS	Weighted Aggregates Sum Product Assessment.

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TAOV	Total Area based on Orthogonal Vectors.
SLR	Systematic Literature Review.
CPS	Criteria Preference Structure.
HSQM	Hierarchical Structure Quality Model.

I. INTRODUCTION

Across the globe, the spread of the novel coronavirus disease (COVID-19) has led to profound changes in social interaction and organizations, and the education sector has not been immune. To maintain social distancing, it was important to revisit traditional education, which gathers many students in one space of implementation. An interesting alternative form of learning that has been promoted due to COVID-19 is online learning [1], [2], [3], [4], [5], [6], [7], [8], [9], [10], [11], [12]. In addition to retaining social distancing, online learning have other numerous benefits such as ease of use, flexibility, better control over the environment, and reduced cost without sacrificing the quality of learning.

As a consequence, many schools across the world are now moving towards online learning and many Web-based E-Learning Platforms (WELPs) such as Blackboard, MOODLE, WebCT, etc. have been introduced by major IT companies. These WELPs are now being explored and evaluated by educational institutions to bring maximum possible ease for their students. Several choices can be made according to the needs of each institution. Hence, to carry out online learning, educational institutions must know how to make a decision on the most appropriate WELP among different alternatives. Evaluating and ranking WELPs involves many diverged quality criteria. Therefore, the selection of the best WELP can be viewed as a complex MCDM problem. In literature, we have noticed that MCDM methods are rarely used for evaluating WELPs. Traditional MCDM methods such as AHP have been applied to solve this issue [13], [14], [15]. However, these methods suffer from additive complexity and inconsistency due to the large number of pairwise comparisons used to estimate the relative weights of evaluation criteria [16], [17], [18], [19]. The purpose of this study is to fill this research gap and propose a Hybrid MCDM (HMCDM) method that helps solve the problem of evaluating and ranking WELPs efficiently.

HMCDM is a promising and more efficient decision-support tool. When using HMCDM in situations with an increasing variety and complexity of information as well as when facing more difficult problems, a decision-maker can be more confident in the outcomes. As a result, a propensity toward hybridization of well-known and other methods to fit for use in a specific application may be seen in state-of-the-art trends in MCDM [20], [22].

The proposed HMCDM approach incorporates different techniques (i.e., BWM, SAW, and Delphi) and comprises the following three phases: 1) the quality criteria of WELPs are defined in a Hierarchical Structure Quality Model (HSQM); 2) the relative weights of the criteria identified in HSQM are estimated using the Best-Worst Method (BWM); this is called a Criteria Preference Structure (CPS); 3) finally, to rank WELPs, the scores of different alternatives over all criteria are estimated and integrated with the CPS using the Simple Additive Weighting (SAW). The relative preferences of criteria and the performance of WELPs over these criteria have been estimated using the widely used consensus method, Delphi. The proposed approach has been validated and compared to AHP, a widely accepted representative to traditional MCDM methods. The results revealed that the proposed method surpasses AHP.

The main contributions of this work are: 1) introducing a HMCDM method that is more efficient and more reliable than traditional MCDM approaches, 2) employing the proposed approach to solve the important and the complex MCDM problem of evaluating and ranking WELPs. The rest of this paper is organized as follows; section II reviews MCDM methods and describes the current related research. In section III, the proposed HMCDM approach is introduced and validated through a use case scenario. The performance of the proposed approach is evaluated and compared to AHP in section IV. In section V, we discuss research findings and highlight research contributions and the strengths and the limitations of HMCDM approach. Finally, in section VI, we give our conclusion remarks and future work.

II. LITERATURE REVIEW

MCDM [74], [75], [76] is concerned with structuring and solving decision making problems involving different alternatives and multiple conflicting evaluation criteria. Over the years, several MCDM methods (estimated to be over one hundred) have been introduced in literature [22], [23], [24], [25], [26], [27], [28], [29], [30], [31], [32], [33], [34], [35], [36], [37], [38], [39], [40], [41], [42], [43], [44], [45], [46], [47], [48], [49], [50], [51], [52], [53], [54], [55]. Although all MCDM methods share the same objective, they employ quite different techniques. There are no better or worse ones, only ones that are better suited to a particular application [40]. Table 1 gives a short assessment of the MCDM methods that are most frequently used today [22].

The creation of innovative MCDM methods does not appear to be a major area of current research because of the enormous number of MCDM methods now in use and the time required for a new method to become widely accepted. Thus, the problem directly related to the enormous variety of distinct MCDM methods is hybridizing the best MCDM techniques to apply for a given application.

HMCDM methods are very promising since they are more efficient and improve users' trust; examples of these methods can be found in [23], [24], [40], and [56]. The approach introduced in this work belongs to the hybrid class with the application to WELPs. HMCDM has the potential to improve all areas of decision-making in engineering [56], healthcare [57], supply chain management [58], sustainable energy [59], green supplier [60], Industry 4.0 [61], and others [21], [22], [23], [24] but is especially beneficial for applications in IT market sectors, where IT product differentiation and selection are often achieved by evaluating similar

TABLE 1. A comparison between various MCDM methods adapted from [22].

Method	advantages	disadvantages
AHP	Simple to use; little data usage; any scale of difficulty can be accommodated by changing the hierarchy structure.	For big problems, a lot of pairwise comparisons are necessary; possibility of inconsistencies.
SAW	Intuitive method with simple algorithm. Able to compensate between variables.	Converting minimizing criteria to maximizing is necessary. Holds potential for unfounded results.
BWM	Lower number of pairwise comparisons. Scalable, more reliable and reduce inconsistencies.	Suitable when a unique best criterion and a unique worst criterion can be identified as reference points for pairwise comparisons.
TOPSIS	Simple computation process. Works with a fundamental ranking.	Suitable when the indicators of alternatives do not vary very strongly. Not considering correlation of attributes.
MOORA	Procedure is fairly easy; attributes are separate; robust approach	The qualitative characteristics are changed into quantitative; comparatively difficult computation method.
ARAS	The utility level is taken into account while ranking options; attributes are independent.	The qualitative attributes should be converted into the quantitative attributes.
WASPAS	Simple computations; the approach considers the problem's positive and negative criteria independently.	Only the minimum (for non-benefit traits) and maximum (for beneficial features) values are taken into account; does not take into account all performance metrics.
TAOV	Relative ease of the process; no limitations regarding the scale of criteria.	Low applicability to conflict resolution.

TABLE 2. A summary of WELPs quality models found in literature and the quality factors adopted in these models.

Quality model	Quality Factors (dimension and criteria) used in the quality model
F. Colace et al. 2006 [13], AHP	Management, Collaborative Approach, Management and enjoyment of interactive learning objectives, Usability, Adaptation of learning path
D.Y. Shee et al. 2008 [14], AHP	Learner Interface, Learning Community, System Content, Personalization
Muhammad et al. 2020 [15], AHP	Content (Timely, Accuracy, Variety of Presentation, Relevant), Usability (User Friendly, Interactive Features, Reliability), Organization (Index, Logo, Links, Navigation), Design (Attractive, Text, Browser Compatibility, Multimedia Elements)
Jabr et al. 2010 [62]	Reusability, Interoperability, Accessibility, and Modularization
Tsigereda et al. 2010 [63]	Content, Reliability, Efficiency, and Functionality
Olsina et al. 2012 [64]	Usability, Reliability, Efficiency, and Functionality.
Djouab et al. 2016 [65]	Functionality (Accuracy, Compliance, Interoperability, Security, Suitability, Accessibility, Scalability), Reliability (Recoverability, Maturity, Fault Tolerance, Availability, Consistency), Usability (Learnability, Understandability, Operability, Navigability), Efficiency (Time Behavior, Resource Utilization), Maintainability (Analyzability, Changeability, Testability, Stability, Traceability), Portability (Adaptability, Installability, Replaceability, Conformance, Co-existence)
Amin et al. 2017 [66]	Usability, Learnability, Understandability, Reliability, Correctness, Testability, Flexibility, Functionality, Portability, Effectiveness, Reusability, Navigability, Maintainability, Security, Efficiency, Privacy
Uppal et al. 2018 [67]	Reliability, Assurance, Tangibles, Empathy, and Responsiveness

products against different evaluation criteria given the DMs' preferences.

In the context of WELPs, several quality models that implement different quality factors have been suggested in literature; these are summarized in Table 2. In review of these models, we have noticed that MCDM methods are rarely used for evaluating WELPs. Some researchers have explored AHP [13], [14], [15], however, the large number of criteria used for evaluating WELPs increases the number of pairwise comparisons needed in AHP. This results in additive computational complexity; moreover, these excessive comparisons are the main source of inconsistency [16], [17].

This paper aims to address the aforementioned problem by introducing a novel HMCDM approach for evaluating and ranking WELPs which is more efficient, scalable, and reliable than AHP. The proposed HMCDM method incorporates different techniques (i.e., BWM, SAW, and Delphi). BWM is a recent pairwise comparisons method that has been proven to be more efficient than other traditional methods in computing the relative weights of criteria; while Delphi is a very common consensus method that is used by DMs to assign values to relative preferences of criteria and to estimate the performance of alternatives over these criteria. Finally, SAW is a simple method used to combine the scores of an alternative over different evaluation criteria into a single scalar score which can be used to rank this alternative among others. The following sub-section briefly describes these techniques as well as AHP as a baseline for comparison.

A. ANALYTICAL HIERARCHICAL PROCESS (AHP)

First, it is necessary to introduce AHP and discuss its shortcomings to show how the proposed HMCDM method overcomes its deficiencies. AHP is not meant for itself, it has been chosen as a common representative for traditional MCDM approaches that rely on the numerous workloads of pairwise comparisons. The procedure for AHP is simple and can be briefly described as follows

Input: a set of evaluation criteria $C = \{c_1, c_2, \ldots, c_n\}$

Output: relative weights of criteria $W = [w_1 w_2 \ldots w_n]$ and Consistency Ratio (CR)

Step 1: Estimate the preference matrix

Pairwise comparisons are performed to estimate the relative preferences of criteria. DM evaluates two criteria c_i *and* c_j at a time in terms of their relative importance w.r.t the goal of the study. Preference values (p_{ij}) from 1 to 9 are used to assign the relative importance of criteria. If criterion c_i is exactly as important as criterion c_j, this pair receives a preference $p_{ij} = 1$ (equal importance). If c_i is extremely more (less) important than c_j, the preference $p_{ij} = 9$ (1/9); all gradations are possible in between. These indices are entered row by row into a preference matrix P (n x n) as illustrated in Equations 1, 2 and 3.

$$P = \begin{bmatrix} p_{11} & \cdots & p_{1n} \\ \vdots & \ddots & \vdots \\ p_{n1} & \cdots & p_{nn} \end{bmatrix} \tag{1}$$

$$p_{ji} = \frac{1}{p_{ij}} \tag{2}$$

$$if\ i = j, p_{ij} = 1 \tag{3}$$

Step 2: Calculate the normalized preference matrix

A normalized pairwise comparison matrix $P'(n \times n)$ is created by dividing each element in P by the sum of the elements in its column. This is shown in Equation 4.

$$p'_{ij} = p_{ij} / \sum\nolimits_{i=1}^{n} p_{ij} \tag{4}$$

Step 3: Calculate the relative weights of the criteria. To get the relative weight w_i of criterion c_i, the mean of each row in P' is calculated as per Equation 5.

$$w_i = \frac{1}{n} \sum\nolimits_{j=1}^{n} p'_{ij} \tag{5}$$

These weights are already normalized as illustrated in Equations 6.

$$\begin{gathered} 0 \le w_i \le 1 \\ \sum\nolimits_{i=1}^{n} w_i = 1 \end{gathered} \tag{6}$$

Step 4: Compute consistency

The consistency of the results of the pairwise comparisons must be checked. According to Saaty [46], if the consistency ratio was less than 10%, then it is acceptable. The Consistency Ratio (CR) is given in Equation 7.

TABLE 3. Relationship between RI and n.

n	1	2	3	4	5	6	7	8	9	10
RI	0	0	0.58	0.9	1.12	1.24	1.32	1.41	1.45	1.49

TABLE 4. Relationship between ξ_{max} and p_{BW}.

p_{BW}	1	2	3	4	5	6	7	8	9
ξ_{max}	0	0.44	1	1.63	2.3	3	3.73	4.47	5.23

$$CR = \frac{CI}{RI} \tag{7}$$

RI: is the random index of consistency which takes different values based on n as shown in Table 3.

CI is consistency index and is given by Equation 8.

$$CI = \frac{\lambda_{max} - n}{n - 1} \tag{8}$$

$\lambda_{\max}$: is the maximum eigenvalue.

B. BEST-WORST METHOD (BWM)

The very significant challenge to AHP method stems from the additive complexity and inconsistency associated with the large number of pairwise comparisons. Therefore, BWM suggested that when considering the preference of c_i over c_j w.r.t some standard, DM does not need to estimate values for all possible comparisons between criterion pairs; in fact, DM need only to consider comparisons to the *Best* and the *Worst* criteria w.r.t the norm in question, these are called reference comparisons, while other comparisons (i.e., secondary comparisons) have no role in estimate of relative weights. BWM can be described as follows:

Input: a set of evaluation criteria $C = \{c_1, c_2, \ldots, c_n\}$

Output: optimal weights of criteria, $W^* = \left[w_1^* w_2^* \ldots w_n^*\right]$, and Consistency Ratio (CR)

Step 1: Determine the best (e.g., most important) criterion, c_B, and the worst (e.g., least important) criterion, c_W, with respect to the goal of comparison.

Step 2: Determine the preference of c_B over all criteria (Best-to-Others) using (1-9) scale. The resulting preference vector is shown in (9):

$$Best - to - Others = [p_{B1} p_{B2} \ldots p_{Bn}] \tag{9}$$

where: $\boldsymbol{p_{Bi}}$ indicates the preference of $\boldsymbol{c}_B$ over $\boldsymbol{c}_i$. It is clear that $\boldsymbol{p_{BB}} = 1$.

Step 3: Determine the preference of all criteria over $\boldsymbol{c}_W$ (Others-to-Worst) using (1-9) scale. The resulting preference vector is shown in (10)

$$Others - to - Worst = [p_{1W} p_{2W} \ldots p_{nW}] \tag{10}$$

where: p_{iW} indicates the preference of c_i over c_W. It is clear that $p_{WW} = 1$.

Step 4: Find the optimal weight of criteria as shown in (11)

$$W^* = \left[w_{1,}^* w_{2,}^* \ldots w_{n,}^*\right] \tag{11}$$

The optimal weight w_i^* for the criterion c_i is the one that satisfies condition (12).

$$\frac{w_B}{w_i} = p_{Bi} \; and \; \frac{w_i}{w_W} = p_{iW} \tag{12}$$

To satisfy these conditions for all $\boldsymbol{i}$, we should solve formula (13) for all $\boldsymbol{i}$.

$$\begin{aligned} &\min_i \max \left(\left|\frac{w_B}{w_i} - p_{Bi}\right|, \left|\frac{w_i}{w_W} - p_{iW}\right|\right) \\ &\text{such that} \sum_{i=1}^{n} w_i = 1 \,, w_i \geq 0, \forall i \end{aligned} \tag{13}$$

The problem in (13) can be transferred into the following problem:

$$\begin{aligned} &\min \boldsymbol{\xi}, \text{such that} \\ &\left|\frac{w_B}{w_i} - p_{Bi}\right| \leq \boldsymbol{\xi} \forall \boldsymbol{i} \\ &\left|\frac{w_i}{w_W} - p_{iW}\right|| \leq \boldsymbol{\xi} \forall \boldsymbol{i} \\ &\sum_{i=1}^{n} w_i = 1, \\ &w_i \geq \mathbf{0}, \forall i \end{aligned} \tag{14}$$

By solving (14), the optimal weights $(w_1^*, w_2^*, \ldots, w_n^*)$ and the optimal value of $\boldsymbol{\xi}$ which is ξ^* can be obtained.

Step 5: compute Consistency Ratio (CR) as per Equation (15) where ξ_{max} varies for different values of p_{BW} as shown in Table 4.

$$CR = \frac{\xi^*}{\xi_{max}} \tag{15}$$

C. SIMPLE ADDITIVE METHOD (SAW)

The Simple Additive Weighting (SAW) is a MCDM method where the performance values of an alternative over multi evaluation criteria are combined in a single scalar score using the weights of the evaluation criteria. If W = $[w_1 w_2 \ldots w_n]$ is the vector representing the weights of evaluation criteria and A = $[a_1 a_2 \ldots a_n]$ is the vector representing the scores of the alternative over all criteria, where a_i is the score of the alternative w.r.t criterion c_i, then the combined score, z, of this alternative can be computed from Equation (16).

$$z = W.A = \sum_{i=1}^{n} w_i a_i \tag{16}$$

D. DELPHI

A well-liked consensus-based estimating technique for classifying and ranking decision-making-related issues is Delphi [68], [69], [70], [71]. In this method, information is gathered from a chosen group of Subject Matter Experts (SMEs) who are competent in a certain subject. Each SME is asked to estimate the relative preferences of criteria and/or performance of alternatives w.r.t criteria. A moderator then presents the estimates from all SMEs in an anonymized manner and has a discussion about them with everyone. The participants are urged to repeatedly reevaluate and adjust their estimate in the light of the comments from earlier discussions until an agreement is reached.

III. THE PROPOSED HMCDM APPROACH

The proposed approach includes the three phases shown in figure 1; these phases are described below.

A. PHASE 1: IDENTIFYING QUALITY EVALUATION CRITERIA FOR WELPs

A Systematic Literature Review (SLR) has been conducted in section II to identify the factors that affect the quality of WELPs. As a result, a broad range of quality factors were identified; furthermore, the identified factors have been classified into main factors (dimensions) and sub-factors (criteria) i.e., related criteria were clustered into a single group called a dimension. The output of this phase is the Hierarchical Structure Quality Model (HSQM) shown in Table 5. It categorizes quality factors into seven dimensions (Functionality, Reliability, Usability, Efficiency, Maintainability, Portability, and Context) which are further sub-divided into 45 criteria that can be used for WELPs evaluation.

B. PHASE 2: PRIORITIZING EVALUATION CRITERIA

Given the HSQM shown in Table 5, we estimate the relative weights of dimensions and criteria (i.e., CPS). First, DMs have implemented a Delphi session which comprises a team of SMEs who have good experience in WELPs; the team consists of five experts; three are academic staff and two are web developers. SMEs have estimated the relative preferences of dimensions and criteria in pairwise comparisons on a scale (1-9). Then, BWM has been used to compute the weights that are shown in Table 6. It must be noted that the relative weights of dimensions are calculated based on pairwise comparisons between dimensions w.r.t the main goal of the study (quality of the WELP). On the other hand, the local weights of criteria are calculated on the basis of pairwise comparisons between criteria within the same dimension w.r.t this dimension. A criterion's overall (global) weight can be obtained by multiplying its local weight by the weight of the dimension to which it belongs. In Table 6, we can verify that the following conditions.

- The sum of the relative weights of all dimensions = 1
- The sum of the local weights of criteria within each dimension = 1
- The sum of the global weights of criteria within a dimension = The weight of this dimension
- The sum of the global weights of all 45 criteria = 1.

From Table 6, we can see that *"Content"* was ranked as the most important dimension with priority 34.4% while the least important dimension was *"Portability"* with priority only 3.3%. Locally, *security"* was ranked as the most important criterion in *"Functionality"* dimension with priority 41%, while *"accuracy"* came in the last place with priority 3.8%.

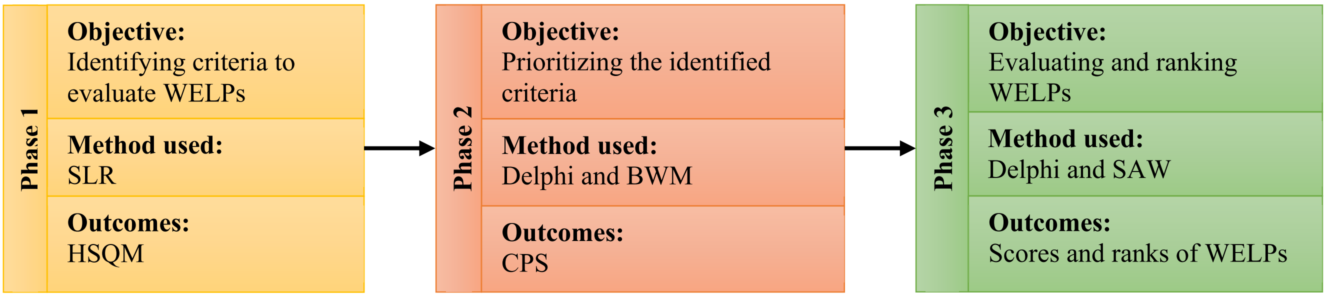

FIGURE 1. **The proposed HMCDM approach for WELPs evaluation.**

For *"Reliability"* dimension, the most important criterion was *"availability"* with weight 39.8%, while the least important criterion was *"maturity"* with weight 3.7%. Within the "Usability" dimension, *"ease of use"* was ranked first with priority 31.4%, while *"operability"* came last with priority only 2.9%. As for *"Efficiency"*, criterion *"resource utilization"* attained the highest priority of 54% followed by *"time behavior"* with priority 29% then *"efficiency compliance"* with priority 17%. For the *"Maintainability"* dimension, *"stability"* was selected as the most important criterion with 35.5% priority and *"analyzability"* was ranked in the last place with 4.3% priority. For *"Portability"* dimension, *"adaptability"* came in the first place with priority 38.6%, while "co-existence" was ranked last with priority 4.6%. Finally, in *"Content"* dimension, *"sufficient content"* was the most important criterion with weight 31%, while *"blogs"* was the least important one with weight 3%. Overall, *"sufficient content"* was ranked as the criterion with the highest priority 10.66%, while "co-existence" was ranked as the least important criterion with priority 0.15%.

C. PHASE 3: EVALUATING AND RANKING WELPs

A set $E = \{e_1, e_2, \ldots, e_m\}$ of m WELPs has to be evaluated and ranked w.r.t a set $C = \{c_1, c_2, \ldots, c_n\}$ of n criteria, where m and n are positive integers. The SAW method is used to evaluate and rank WELPs as described below:

Input: a set of WELPs, E, and a set of evaluation criteria C

Output: Ranking of E.

Step 1: Build a decision matrix, X.

DMs create X ($n \times m$) in which they rate the performance of each WELP in E over all criteria in C.

$$X = \begin{bmatrix} x_{11} & \cdots & x_{1m} \\ \vdots & \ddots & \vdots \\ x_{n1} & \cdots & x_{nm} \end{bmatrix} \tag{17}$$

x_{ij} : score of WELP e_j w.r.t. criterion c_i
$i = 1, 2, \ldots, n$ and $j = 1, 2, \ldots, m$

Step 2: Determine the normalized decision matrix, Y.

Y ($n \times m$) are calculated as follows:

For beneficial criterion

$$y_{ij} = \frac{x_{ij}}{x_i^{max}} \tag{18}$$

For non-beneficial criterion

$$y_{ij} = \frac{x_i^{min}}{x_{ij}} \tag{19}$$

where $\boldsymbol{y_{ij}}$ is the normalized score of WELP $\boldsymbol{e_j}$ w.r.t. criterion $\boldsymbol{c_i}$,

$$x_i^{max} = \max_j (x_{ij}) \tag{20}$$

$$x_i^{min} = \min_j (x_{ij}) \tag{21}$$

Step 3: Compute the overall score for each WELP

The overall score of a WELP $\boldsymbol{e_i}$ is

$$s_j = \sum\nolimits_{j=1}^{n} w_i y_{ij} \tag{22}$$

Equivalently, the overall score vector $S = [s_1 s_2 \; s_m]$ can be computed as follows:

$$S = WY \tag{23}$$

Step 4: Rank S.

The best WELP is the one with the highest score in S.

Next, we validate the proposed HMCDM approach through the following use case scenario:

Five (m=5) WELPs, all involving English learning, have been evaluated using (n=45) criteria defined in Table 5. The selected WELPs were denoted $E = \{e_1, e_2, e_3, e_4, e_5\}$ to protect their anonymity. The SMEs were invited to another Delphi session to estimate the performance of each WELP w.r.t every criterion on scale 1-to-100 (lowest to highest) and the moderator fed the final scores into the decision matrix X. There are a total of 225 elements in X (45×5); the normalized decision matrix Y (45×5) was computed from Equation 18; X and Y are shown in Table 7 and Table 8 respectively. Finally, each WELP's overall score is acquired by summing its weighted performance scores over all criteria as per Equations 22, 23; the resulting score vector S is shown below.

$$S = [81.28 \; 85.64 \; 69.72 \; 97.52 \; 88.63]$$

The results in S show that the best WELP is e_4 with score 97.52; the other WELPs are ranked as follows: in the second place came e_5 with score 88.63, e_2 was ranked third with score 85.64, e_1 was ordered in the fourth place with score 81.28, and finally, e_3 came in the last place with score 69.72.

TABLE 5. Quality factors (dimensions and criteria) for WELPs evaluation (HSQM).

Quality Factor	Short definition
D1: Functionality	set of functions that WELP can provide for the user
c_1: Suitability	degree of appropriateness and completeness of provided functions
c_2: Accuracy	ability to provision of right or agreed results or effects
c_3: Interoperability	ability of WELP to interact to other systems or applications
c_4: Security	ability to protect data confidentiality and integrity
c_5: Accessibility	WELP can be used by all people regardless of disability with the widest range of functions
c_6: Scalability	ability to sustain good performance when data volume is changed
c_7: Functional Compliance	adherence to functionality related standards or conventions
D2: Reliability	ability to performs specified functions under specified conditions for specified time
c_8: Maturity	frequency of failure by faults
c_9: Fault Tolerance	ability to preserve a specified level of performance despite the presence of faults
c_{10}: Recoverability	ability of reestablish level of performance after failure
c_{11}: Availability	degree to which WELP is operational and accessible when required for use
c_{12}: Consistency	lack of contradiction among results
c_{13}: Reliability Compliance	degree to adherence to reliability related standards
D3: Usability	degree to which WELP can be used by specified users with satisfaction
c_{14}: Understandability	ability of user to recognize the structure and applicability of WELP
c_{15}: Learnability	ability of user for learning usage of WELP
c_{16}: Operability	ability of user for operation and operation control
c_{17}: Attractiveness	degree of being pleasing to the user
c_{18}: Navigability	ability to flow through WELP without being frustrated
c_{19}: Ease of use	percentage of users who were able to successfully learn how to use WELP
c_{20}: Cost of use	cost of owning and running WELP
c_{21}: Usability Compliance	degree to adhere to usability related standards
D4: Efficiency	ratio of useful utilization of time and resources
c_{22}: Time Behavior	response and proceeding time and throughput rates
c_{23}: Recourse Utilization	number of resources used and the duration of such use
c_{24}: Efficiency Compliance	degree to adhere to efficiency related standards
D5: Maintainability	degree to which WELP can be modified or improved as per changes in environment
c_{25}: Analyzability	ability to identify deficiency, failure causes, and modules to be modified
c_{26}: Changeability	ability to implement modifications, fault removal or environmental changes
c_{27}: Testability	ability to validate modifications
c_{28}: Stability	risk of unexpected effect of modifications
c_{29}: Traceability	ability to trace faults and modifications forward and backward through the development lifecycle
c_{30}: Maintenance Compliance	degree to adhere to maintenance related standards
D6: Portability	degree to which WELP can be transferred from one operational or usage environment to another
c_{31}: Adaptability	ability of WELP to adapt for different or evolving operational or usage environments
c_{32}: Installability	ability to install WELP in a given environment
c_{33}: Replaceability	degree to which a module can replace another for the same purpose in the same environment
c_{34}: Conformance	degree to which WELP meets expectations and desired criteria
c_{35}: Co-existence	ability of WELP to perform efficiently while sharing a common environment with other products
c_{36}: Portability Compliance	degree to adhere to portability related standards
D7: Content	materials and tools related to courses and curriculum
c_{37}: Up-to-date content	degree to which content has the most recent information
c_{38}: Sufficient content	degree to which content suffices user's need
c_{39}: Relevant content	degree to which content meets user's interest
c_{40}: Presentation of Content	degree to which content presentation is seamless and clear to user
c_{41}: Assessment tools	abundancy of assessment tools such as quizzes, exams, homework, assignments, etc.
c_{42}: Surveys and Questionnaire	ability of users to give feedback through collection instruments and tools for statistical analysis
c_{43}: Interactive discussions	ability of students and teachers to discuss contents online
c_{44}: Comm. & Messaging	ability of users to communicate through email, chats, etc.
c_{45}: Blogs, Wikis	ability of students and instructors to share content through web-based platforms

IV. PERFORMANCE EVALUATION

In this section, the performance of the proposed HMCDM is compared to traditional approaches (i.e., AHP). The simulation of AHP has been accomplished using the tool in [72]. BWM computations have been put into practice using the BWM Linear Solver [73].

Table 9 compares HMCDM to AHP in terms of number of pairwise comparisons used in each approach. It shows that while AHP required 154 comparisons to complete the whole evaluation process, HMCDM needed only 80 with a reduction of 48%. Figure 2 shows that for ($n > 3$), HMCDM requires fewer pairwise comparisons than AHP; it also shows that number of pairwise comparisons rapidly increases with n when using AHP, while it increases slowly with HMCDM; this clearly illustrates the scalability of HMCDM. Figure 3 shows the percentage reduction in pairwise comparisons at different values of n when HMCDM is used. From Figures 2 and 3, we can conclude that HMCDM is more efficient than

TABLE 6. Weights of dimensions and local and global weights of criteria (CPS).

Dimension	% weight	Criterion	% local weight	% global weight
D1: Functionality	13.2	c_1: Suitability	8	1.06
		c_2: Accuracy	3.8	0.5
		c_3: Interoperability	9.6	1.27
		c_4: Security	41	5.41
		c_5: Accessibility	16	2.11
		c_6: Scalability	12	1.58
		c_7: Functional Compliance	9.6	1.27
D2: Reliability	7.9	c_8: Maturity	3.7	0.29
		c_9: Fault Tolerance	11.6	0.92
		c_{10}: Recoverability	15.5	1.22
		c_{11}: Availability	39.8	3.14
		c_{12}: Consistency	17.8	1.41
		c_{13}: Reliability Compliance	11.6	0.92
D3: Usability	9.9	c_{14}: Understandability	12.3	1.22
		c_{15}: Learnability	18.4	1.82
		c_{16}: Operability	2.9	0.29
		c_{17}: Attractiveness	9.2	0.91
		c_{18}: Navigability	12.3	1.22
		c_{19}: Ease of use	31.4	3.11
		c_{20}: Cost of use	7.4	0.73
		c_{21}: Usability Compliance	6.1	0.6
D4: Efficiency	18.1	c_{22}: Time Behavior	29	5.25
		c_{23}: Recourse Utilization	54	9.77
		c_{24}: Efficiency Compliance	17	3.08
D5: Maintainability	13.2	c_{25}: Analyzability	4.3	0.57
		c_{26}: Changeability	11.8	1.56
		c_{27}: Testability	12.9	1.70
		c_{28}: Stability	35.5	4.69
		c_{29}: Traceability	16.1	2.13
		c_{30}: Maintenance Compliance	19.4	2.56
D6: Portability	3.3	c_{31}: Adaptability	38.6	1.27
		c_{32}: Installability	12	0.40
		c_{33}: Replaceability	13.8	0.46
		c_{34}: Conformance	10.3	0.34
		c_{35}: Co-existence	4.6	0.15
		c_{36}: Portability Compliance	20.7	0.68
D7: Content	34.4	c_{37}: Up-to-date content	11.6	3.99
		c_{38}: Sufficient content	31	10.66
		c_{39}: Relevant content	8.7	2.99
		c_{40}: Presentation of Content	6.9	2.37
		c_{41}: Assessment tools	11.6	3.99
		c_{42}: Surveys and Questionnaire	8.7	2.99
		c_{43}: Interactive discussions	6.9	2.37
		c_{44}: Comm. & Messaging	11.6	3.99
		c_{45}: Blogs, Wikis	3	1.03

AHP since it requires less comparisons and consequently less computational work.

The consistency ratio (CR) gauges the reliability of a MCDM method's output; CR for AHP and HMCDM can be computed from equation 7 and 15 respectively. The CR scales from 0 to 1, with values closer to 0 (0%) exhibiting greater consistency and values closer to 1 (100%) exhibiting lesser consistency. The pairwise comparison matrix's judgments are totally consistent if CR is equal to 0, and adequate consistency is indicated by a CR of less than 10%. Table 10 shows a comparison between AHP and HMCDM in terms of CR. As expected, due to the removal of secondary comparisons, HMCDM has smaller CR than AHP, thus, it is more reliable. The results show an average improvement of 53.39%.

V. DISCUSSION

From the analysis of the experimental results, we conclude that the strengths of the proposed HMCDM over traditional MCDM approaches lie in: **1) Efficiency;** considering that fewer comparisons (just the reference comparisons) need to be submitted and processed, the proposed approach involves less computation workload that traditional approaches. Number of required pairwise comparisons in the proposed approach = *(n-2)* Best-to-Others + *(n-2)* Others-to-Worst + *(1)* Best-to-Worst = $2n$-3 instead of $n(n-1)/2$ in AHP, **2) Reliability;** due to the exclusion of secondary comparisons in the proposed approach, comparisons become more reliable; secondary comparisons are more challenging, less precise, and ideally redundant; they are the primary cause

TABLE 7. Decision matrix, X.

	e_1	e_2	e_3	e_4	e_5
c_1	82	63	56	85	71
c_2	85	67	67	80	76
c_3	53	81	63	94	80
c_4	64	65	71	92	95
c_5	85	78	72	88	83
c_6	73	64	55	82	89
c_7	68	66	64	87	75
c_8	59	70	85	80	77
c_9	65	78	52	91	82
c_{10}	71	82	57	78	81
c_{11}	75	77	63	82	85
c_{12}	78	72	71	89	77
c_{13}	86	78	60	95	80
c_{14}	83	65	52	80	79
c_{15}	72	80	58	93	75
c_{16}	74	64	85	82	76
c_{17}	85	68	66	88	68
c_{18}	77	85	52	81	72
c_{19}	65	75	57	84	83
c_{20}	62	68	68	79	70
c_{21}	70	88	70	80	74
c_{22}	92	81	50	80	72
c_{23}	72	85	67	82	76
c_{24}	82	70	63	86	65
c_{25}	88	72	61	75	84
c_{26}	76	73	59	89	74
c_{27}	66	63	54	80	85
c_{28}	58	70	49	93	78
c_{29}	81	61	57	91	83
c_{30}	83	83	66	81	89
c_{31}	73	63	69	86	77
c_{32}	67	72	57	86	90
c_{33}	78	61	73	88	80
c_{34}	69	55	64	94	95
c_{35}	88	60	51	95	70
c_{36}	55	88	59	87	72
c_{37}	62	63	68	88	66
c_{38}	64	88	65	87	78
c_{39}	68	78	72	89	85
c_{40}	85	59	68	83	75
c_{41}	85	83	60	95	88
c_{42}	72	75	55	96	84
c_{43}	80	92	45	90	76
c_{44}	61	74	62	91	72
c_{45}	65	90	65	82	82

TABLE 8. Normalized decision matrix, Y.

	e_1	e_2	e_3	e_4	e_5
c_1	0.9647	0.7412	0.6588	1	0.8353
c_2	1	0.7882	0.7882	0.9412	0.8941
c_3	0.5638	0.8617	0.6702	1	0.8511
c_4	0.6737	0.6842	0.7474	0.9684	1
c_5	0.9659	0.8864	0.8182	1	0.9432
c_6	0.8202	0.7191	0.618	0.9213	1
c_7	0.7816	0.7586	0.7356	1	0.8621
c_8	0.6941	0.8235	1	0.9412	0.9059
c_9	0.7143	0.8571	0.5714	1	0.9011
c_{10}	0.8659	1	0.6951	0.9512	0.9878
c_{11}	0.8824	0.9059	0.7412	0.9647	1
c_{12}	0.8764	0.809	0.7978	1	0.8652
c_{13}	0.9053	0.8211	0.6316	1	0.8421
c_{14}	1	0.7831	0.6265	0.9639	0.9518
c_{15}	0.7742	0.8602	0.6237	1	0.8065
c_{16}	0.8706	0.7529	1	0.9647	0.8941
c_{17}	0.9659	0.7727	0.75	1	0.7727
c_{18}	0.9059	1	0.6118	0.9529	0.8471
c_{19}	0.7738	0.8929	0.6786	1	0.9881
c_{20}	0.7848	0.8608	0.8608	1	0.8861
c_{21}	0.7955	1	0.7955	0.9091	0.8409
c_{22}	1	0.8804	0.5435	0.8696	0.7826
c_{23}	0.8471	1	0.7882	0.9647	0.8941
c_{24}	0.9535	0.814	0.7326	1	0.7558
c_{25}	1	0.8182	0.6932	0.8523	0.9545
c_{26}	0.8539	0.8202	0.6629	1	0.8315
c_{27}	0.7765	0.7412	0.6353	0.9412	1
c_{28}	0.6237	0.7527	0.5269	1	0.8387
c_{29}	0.8901	0.6703	0.6264	1	0.9121
c_{30}	0.9326	0.9326	0.7416	0.9101	1
c_{31}	0.8488	0.7326	0.8023	1	0.8953
c_{32}	0.7444	0.8	0.6333	0.9556	1
c_{33}	0.8864	0.6932	0.8295	1	0.9091
c_{34}	0.7263	0.5789	0.6737	0.9895	1
c_{35}	0.9263	0.6316	0.5368	1	0.7368
c_{36}	0.625	1	0.6705	0.9886	0.8182
c_{37}	0.7045	0.7159	0.7727	1	0.75
c_{38}	0.7273	1	0.7386	0.9886	0.8864
c_{39}	0.764	0.8764	0.809	1	0.9551
c_{40}	1	0.6941	0.8	0.9765	0.8824
c_{41}	0.8947	0.8737	0.6316	1	0.9263
c_{42}	0.75	0.7813	0.5729	1	0.875
c_{43}	0.8696	1	0.4891	0.9783	0.8261
c_{44}	0.6703	0.8132	0.6813	1	0.7912
c_{45}	0.7222	1	0.7222	0.9111	0.9111

of contradiction, **3) Scalability;** the proposed approach can manage larger number of criteria without sacrificing efficiency. The contributions of this study are, thus, 1) the introduction of an HMCDM that is more effective, dependable, and scalable than traditional MCDM approaches, and 2) the use of the suggested approach to resolve the significant and challenging MCDM problem of evaluating WELPs.

On the other hand, the main limitation of this study is that it adopts a subjective method that relies on DMs' preferences to determine the weights of evaluation criteria. Since Different DMs weigh criteria differently, the selected solution is subject to the preferences of DMs and typically, there is no unique optimal solution. To overcome this problem, we plan to employ an objective approach for determining the weights of criteria. This method views the criteria as sources of information. The relative relevance of the criteria

TABLE 9. HMCDM vs. AHP in terms of no. of pairwise comparisons.

Dimensions/Criteria	n	no. of pairwise comparisons	
		AHP	HMCDM
All Dimensions	7	21	11
Functionality	7	21	11
Reliability	6	15	9
Usability	8	28	13
Efficiency	3	3	3
Maintainability	6	15	9
Portability	6	15	9
Content	9	36	15
Total no. of pairwise comparisons		**154**	**80**
% reduction in pairwise comparisons		**48%**	

TABLE 10. HMCDM vs. AHP in terms of CR.

Dimensions/Criteria	Consistency Ratio (% CR)	
	AHP	HMCDM
All Dimensions	12.7	5.11
D1	8.8	6.94
D2	14.8	6.73
D3	9.7	5.42
D4	4.2	4.17
D5	9.8	3.23
D6	9.3	2.75
D7	12.2	3.65
Average %CR	**10.19**	**4.75**
% improvement in CR	**53.39 %**	

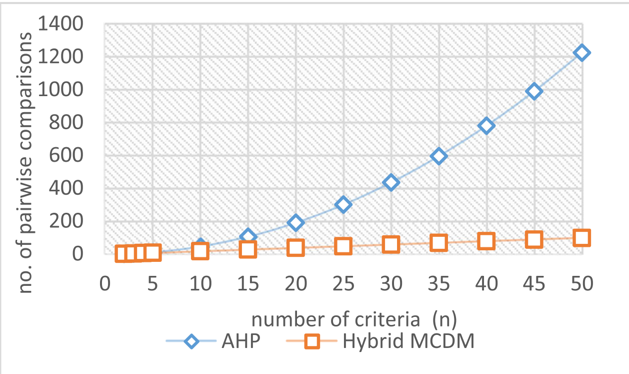

FIGURE 2. Number of comparisons in AHP and HMCDM.

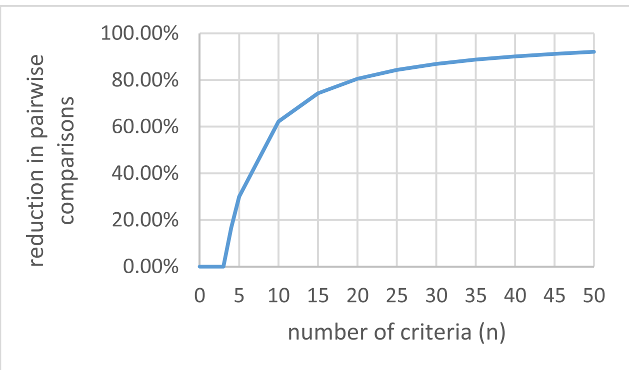

FIGURE 3. % reduction in number of pairwise comparisons due to HMCDM.

shows the quantity of information that each criterion has. The degree of contrast between each criterion and the amount of information it contains is correlated. Possible indicators of the strength and modes of presentation of objective criteria weight are the standard deviation and entropy.

VI. CONCLUSION AND FUTURE WORK

Many educational institutions have investigated the usage of WELPs as a replacement to regular classrooms. However, it has rarely been considered as the main scheme of formal education until the spread of COVID-19. Hence, teaching is now moving to WELPs on an unprecedented scale. This paper addresses the problem of selecting the WELP that best fits the needs of educational institutions. Since the solution to this problem involves evaluating different alternatives using multiple conflicting evaluation criteria, it has been treated as a MCDM problem. We introduced a HMCDM approach that incorporates different techniques (i.e., Delphi, BWM and SAW) to evaluate WELPs. The proposed approach outperforms AHP in terms of efficiency, scalability, and reliability.

The applications of HMCDM techniques for industry are becoming more well-known. One of the most promising future directions is the application of HMCDM in Industry 4.0 area. Other promising research directions that we plan to explore is the application of HMCDM in IoT and green computing.

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