

Selection and Ranking of E-Learning Websites using MCDM based EDAS Technique

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Abstract: This study assesses and orders E-learning websites using predefined evaluation criteria. Employing MCDM methodology, it ranks these websites based on divergent assessment indices. The task of selecting E-learning platforms is tackled using Weighted-Evaluation based on Distance from Average Solution (W-EDAS), a MCDM algorithm tailored for such challenges. To validate its effectiveness, the results obtained from this method are compared with those from established approaches like Fuzzy COPRAS. Importantly, the proposed methodology has not been previously utilized to evaluate, select, and rank various E-learning websites.

Keywords: *E-Learning websites, Shannon Entropy, Weighted Evaluation based on Distance from Average Solution (W-EDAS), Selection & Ranking, MCDM*

Introduction

E-learning, short for electronic learning, refers to courses delivered and designed electronically. In simpler terms, it provides learners access to a technologically advanced learning environment, typically via the Internet. The most common approach to achieve this is through a learning platform that directly delivers content to the learner. However, the method may vary depending on the platform and available content. Early online courses, for instance, were often text-based with occasional diagrams and graphics. These courses served as substitutes for textbooks and were easily updatable compared to printed materials, which required reprinting for updates.

As e-learning evolved, the adoption of new media and technology surged. Nowadays, one can benefit from online courses featuring in-depth videos offering detailed explanations and examples relevant to the subject matter. Furthermore, it facilitates learning through carefully curated podcasts and audio segments for students.

However, this represents just a fraction of the innovative ways e-learning leverages technology to enhance the learning experience for both students and educators. Virtual reality stands as one of the most ambitious ventures in e-learning today, yet its widespread acceptance is hindered by the technological requirements and challenges it presents. Nevertheless, in K–12 education settings, the human connection remains indispensable for a child's development and cannot be easily replaced.

Under the circumstances, online learning is beneficial as a complement in academic and professional settings.[16]

Factors that contribute toward a good learning website:

1. **Cost-effectiveness:** The company's potential to save money and the benefits it would derive from it would account for a sizable portion of the company's e-value learning (improves job performance, enhances skill and knowledge, and impacts results). It was claimed to be economical.
2. According to Quality Reference [20], the four quality categories are response, learning, performance, and outcomes. Performance was the assessment, based on questions presented to e-learners who had completed the online learning. In contrast, Reaction was the standard rating sheet. Learning was only a monitoring technique. Ultimately, conclusions were usually requested in

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terms of e-effectiveness learning and superiority to alternative ways

3. Service is still another essential component of e-learning in terms of its caliber and accessibility.

4. Speed is the final and fourth need. There are three crucial factors to consider: When will the e-learning project be implemented? (The development issue.) How soon will initiatives to advance online education be able to reach everyone who requires the knowledge? (The delivery dilemma) The third consideration is how quickly the e-learning project may be changed in response to a corporate change or the requirement to give new or updated knowledge.

In this research, a hierarchy is developed for identifying the various evaluation indexes or sub-indexes for selecting the E-learning website. This research paper includes the preceding notable points: (i) a review of relevant past studies, (ii) a description of the methods to be used, (iii) an empirical study for the current problem, (iv) methodology validation, (v) results in and (vi) significance of proposed method. (vii) the results derived from the current research.

Literature Review

Numerous studies have addressed to confront the difficulty of identifying e-learning websites.

Garg() evaluates, selects, and ranks E-learning websites on the basis of Euclidean distance (weighted). It also created a computational quantitative approach. The top website is ranked number one. There are several qualities and ranking factors in the decision-making problem Webpage Selection, Evaluation, and Ranking. This study used 5 important E-learning websites to assess the model's usability, and technique endorsement.[1]

Volery and Lord () recognized three essential factors in online delivery: (i) technology (accessibility, interface design, and engagement level); (ii) teacher (attitudes towards students, technical expertise, and classroom interaction); and (iii) student technological experience.[2]

Prougestaporn et al. () proposed four e-learning success elements and four assessment criteria. E-learning and distant learning are possible online. E-learning may be advantageous for higher education since students may learn anywhere, anytime. Evaluative variables affect higher education e-learning. This research analyses e- efficacy

learning criteria in higher education. [3]

Saowapakpongchai et al.() investigated the use of E-Learning in Thai higher educational institutions. Both academic professionals and students participated in the literature evaluation and analysis. Human consideration, instructional design, the advancement of technology, and social interaction are all incorporated within 4D eLearning.[4]

Pruengkarn et al. () evaluated Thai educational institutions' e-learning websites using predetermined criteria. This research project evaluated quality attributes such as functionality, dependability, usefulness, efficiency, maintainability, and portability. This research will also examine two new quality criteria. The findings show that e-learning websites have an average quality of 50.34 percent, which Webmasters can use to evaluate and improve their websites by the proposed quality model to make e-learning more effective. E-learning efficacy may also be measured by website quality[5].

Cevic et al. () provided a high-level overview of the significant prerequisites and issues for developing a system in the context of E-learning. This study addressed the limits of today's generation of recommendation approaches and prospective extensions, such as model tag-based recommender systems for tagging activities that can be utilized to improve recommendation capabilities in e-learning environments [6].

Rajab() combined the results of two effective feature selection procedures to develop a new feature score (IG, CHI). The new methodology created a new normalised score during the phishing dataset preparation stage. The results of applying the approach, CHI, and IG to 30 security characteristics stated that the new method is capable of selecting relevant parameters that influence phishing detection rates [7].

Smith() created evaluation criteria for government websites, which they applied to a sample of "four websites representing NZ government agencies." [8].

Yasmina et al. () examined how big data analytics (BDA) skills affect firm performance using multi-factor decision-making (MCDM). IF-DEMATEL, ANP, and simple additive weighting were utilized in this investigation (SAW). BDA capabilities affect operational performance more than market

performance [9].

Naveed et al. () examined E-Learning CSFs, which are cloud-based, for education and training. First, combinatorial analysis analyzed CSFs and various learning dimensions, which are cloud-based. This system evaluated cloud-based E-Learning CSFs. This study discovered fourteen elements in four directions. Next, the combinatorial analysis determined how much each component affected output[10].

Gong et al. () highlighted our LHFS-TODIM integrated MCDM system. This strategy searched for and implemented the most excellent network teaching e-learning website. LHFSs examine professionals' language abilities, the best-worst method (BWM) weights evaluation criteria, and an updated TODIM approach ranks e-learning websites in this new method [11].

Basset et al. () suggested multi-criteria decision-making (MCDM) criteria whose components are defined by various attributes, and each of them can have multiple values. This model was made using AHP, VIKOR, and TOPSIS. Financial ratios were compared to determine economic performance. Here, Egypt's ten largest steel businesses are compared using financial criteria to evaluate the methodology [12].

Naveed et al. () used AHP, GDM, and FAHP for examining the multiple criteria of the web-based E-Learning system. This research shows CSF dimensions and quantifications. After finding them in the literature, the authors further investigated the five distinct dimensions and twenty-five parts of the web-based E-Learning system. [13].

Anvari and Sotoudeh() reviewed high-impact, peer-reviewed journal articles on COVID-19 MCDM methods and found that fuzzy sets in MCDM approaches are promising COVID-19 research. [14]

Güldeş et al. () established parameters for application study LMS system development. FAHP employed multi- criteria. The author used seven metrics and thirty-one metrics to assess e-learning platforms. Most important were Security (C3), Quality (C6), and Material (C7) (C4). Account, assessment, and exam result security (C3) is of the utmost importance.[15]

The literature shows that assessing e-learning websites is an MCDM challenge with contradicting selection indices. Existing techniques like VIKOR,

AHP, TOPSIS, and DBA have drawbacks, including additional pair-by-pair comparisons, reliance on expert judgment for data gathering, discrepancy owing to the interrelation of selection indices, or for considering the priority weights for selection indices. This method employs W-EDAS to represent the challenge to select e-learning websites as an MCDM problem. The strategy and approach proposed are validated by ranking the eight most popular websites globally [3, 19]. It was concluded that a hybrid model based on W-EDAS could assist pupils and developers grade these websites. THE

METHODOLOGY: W-EDAS

The present study proposes the W-EDAS technique, which combines the Shannon Entropy approach and the EDAS method, for optimizing e-learning websites. To understand better, the steps are listed below:

Shannon Entropy Approach

Shannon's Entropy technique [19] sequences the weight given to the computation of the performance indices used in every deciding criteria. A matrix is produced, which forms the basis for the weight computation, once ratings for all performance metrics have been collected for each option. The steps for implementing this technique are as follows:

Let $[A_{ij}]_{m \times n}$ be the decision matrix. The size of the decision matrix is $[m \times n]$, where the number of alternatives is denoted by "m" and performance indexes by "n".

$$[A_{ij}]_{m \times n} = \begin{matrix} & \begin{matrix} n_1 & n_2 & \dots & n_n \end{matrix} \\ \begin{matrix} m_1 \\ m_2 \\ \vdots \\ m_n \end{matrix} & \begin{bmatrix} A_{11} & A_{12} & \dots & A_{1n} \\ A_{21} & A_{22} & \dots & A_{2n} \\ \vdots & \vdots & \dots & \vdots \\ A_{m1} & A_{m2} & \dots & A_{mn} \end{bmatrix} \end{matrix}$$

Eq. 1 normalizes the decision matrix.

$$norm[A_{ij}]_{m \times n} = \frac{A_{ij}}{\sum_{i=1}^m A_{ij}} \quad (1)$$

The next step is to calculate the entropy value for each n (performance index), which can be done using eq. (2)

$$E_{ij} = -k \sum_{j=1}^n norm[A_{ij}] (\ln(norm[A_{ij}])) \quad (2)$$

$$\text{Where } k = \frac{1}{\ln(n)}$$

The priority weights are calculated using eq (3) for

all the performance indexes(n).

$$[w]_{i \times m \times 1} = \frac{E_i}{\sum_{i=1}^m E_i} \quad (3)$$

Evaluation based on Distance from the Average Solution (EDAS)

Ghorabae et al.[18] have created a methodology called EDAS for multi-criteria stock characterization. MCDM problems can be better dealt with through this EDAS approach. Conversely, an alternate solution in the approach that the authors suggested is related to the distance from the average solution (AVS). Two metrics are computed as the foundation of the EDAS approach.

The initial step is to find the positive distance from the average (PDAVS). The second step is to find the negative distance from the average (NDASV). These metrics illustrate differences between each alternate option and the average answer. The evaluated alternate solutions are based on greater PDAVS values and lower NDASV values. The solution (alternative) is better than the average solution if PDAVS is higher and/or NDASV is lower. Assuming there are k decision-makers (D = D1,D2,..., Dk), a set of mcriteria (C = c1, c2,..., cm), and a set of n options (A = A1, A2,..., An). the proposed methodology EDAS has been implemented in software reliability for the first time. The step-by-step procedure of the current methodology is illustrated in Figure 5.4.



Figure 1: Flow chart of EDAS methodology
Step 1: Select the most essential criterion for comparing alternatives.

Step 2: Devise the decision-making matrix (Aij), depicted as follows:

$$[A] = [A_{ij}]_{n \times m} = \begin{bmatrix} A_{11} & A_{12} & \dots & A_{1m} \\ A_{21} & A_{22} & \dots & A_{2m} \\ \vdots & \vdots & \ddots & \vdots \\ A_{n1} & A_{n2} & \dots & A_{nm} \\ \vdots & \vdots & \ddots & \vdots \end{bmatrix} \quad (4)$$

Where, Aij denotes the performance value of the ith option based on the jth criterion.

Step 3: Find the average solution (AVS) over every criterion listed below:

$$AVS = [AVS_j]_{1 \times m} = \frac{\sum_{i=1}^n A_{ij}}{n} \quad (5)$$

Step 4: Compute the positive distance (PDAVSij) and the negative distance (NDASVij) from the average solution:

If jth criteria is beneficial, then:

$$PDAVS_{ij} = \frac{\max(0, (A_{ij} - AVS_j))}{AVS_j} \quad (6)$$

$$NDASV_{ij} = \frac{\max(0, (AVS_j - A_{ij}))}{AVS_j} \quad (7)$$

If jth criteria is non-beneficial, then:

$$PDAVS_{ij} = \frac{\max(0, (AVS_j - A_{ij}))}{AVS_j} \quad (8)$$

$$NDASV_{ij} = \frac{\max(0, (A_{ij} - AVS_j))}{AVS_j} \quad (9)$$

Step 5: For each alternative, the weighted sum of positive distance and the weighted sum of negative distance from the average solution are computed:

$$WSP_i = \sum_{j=1}^m W_j * PDAVS_{ij} \quad (10)$$

$$WSN_i = \sum_{j=1}^m W_j * NDAVS_{ij} \quad (11)$$

where w_j represents the weight of j th criterion.

Step 6: WSP_i and WSN_i values are normalized for all alternatives, shown as follows:

$$NWSP_i = \frac{WSP_i}{\max_i(WSP_i)} \quad (12)$$

$$NWSN_i = 1 - \frac{WSN_i}{\max_i(WSN_i)} \quad (13)$$

Step 7: Appraisal score ($APSi$) for all alterna

$$APSi = \frac{1}{2} (NWSP_i + NWSN_i) \quad (14)$$

where, $0 \leq APsi \leq 1$

Step 8: The alternatives are ranked by their decreasing appraisal score ($APSi$) values. Among the candidature options, the candidate with the greatest AS score is the best choice.

An Illustrated Example

Using the EDAS methodology, the following stages evaluate and rank several e-learning websites for the C programming language based on a variety of selection indices.

1) Identification and Selection of E-Learning Websites: The most commonly used websites for learning the C programming language were identified by studying the available literature. A team of five decision-makers who are familiar with the C programming language and working with IT companies or academic institutions for at least the past ten years conducted brainstorming sessions in which the mutually exclusive and collectively exhaustive (MECE) principle and an elimination approach were used to shortlist websites for the research. These were: cprogramming.com; cs.cf.ac.uk; programiz.com; geeksforgeeks.org; tutorialpoint.com; fresh2refresh.com; howstuffworks.com and cprogrammingexpert.com.

2) Identification of Selection Indices: Ten potential selection indices— usability,

functionality, system content, ease of learning, portability, efficiency, maintainability, personalization, reliability, community, and general factors—were used to evaluate, rank, and select these websites.

3) Determination of Weights and Performance Ratings: Website selection index weights are determined using

(3) and (4).

4) Determination of Weights and Performance Ratings: Website performance ratings are determined using (3) and (4).

8.2	8.2	7.4	8.2	8.4	7.8	7.4	6.8	7.4	8.53
4.26	4.06	4.26	4.06	3.2	3.2	4.26	4.06	4.06	4.26
7.6	7.8	7.8	7.2	7.4	7.8	8.2	8.4	8.13	7.6
6.2	6.2	5.4	5.8	6	5.2	4.2	4.4	4.2	
8.73	8.93	8.87	8.4	8.87	8.6	8.87	7.8	8.2	8.4
6.6	7	7.6	5.8	6.4	6.4	6.6	6.4	6.4	
8.53	8.2	8.87	8.53	8.6	8.73	8	8.33	8.2	7.6
4.8	5	4.8	5	4.13	4.8	4.13	5	4.13	4.13

allow:

5) Determine the average solution (AVS): Equation (5) determines the average solution of each e-learning website.

6) Calculate the positive distance (PDAVS_{ij}) and the negative distance from average solution (NDAVS_{ij}): Equations (06) and (07) are used to determine the PDAVS_{ij} and NDAVS_{ij} of each e-learning website and are shown below:

0	0	0	0	0	0	0	0	0	0
0.365599	0.413613	0.389247	0.382392	0.515152	0.51997	0.350362	0.365501	0.362137	0.3333333333
0	0	0	0	0	0	0	0	0	0
0.255398	0.104532	0.111111	0.178551	0.121212	0.099944	0.207015	0.343622	0.308072	0.342723005
0	0	0	0	0	0	0	0	0	0
0.017126	0	0	0.117705	0.030303	0.03994	0.024018	0	0	0
0	0	0	0	0	0	0	0	0	0
0.285182	0.277048	0.311828	0.239399	0.374242	0.279955	0.370187	0.218597	0.351139	0.353671621
0.221147	0.184329	0.060932	0.247385	0.272727	0.170073	0.128479	0.062708	0.162308	0.334898279
0	0	0	0	0	0	0	0	0	0
0.131794	0.126657	0.11828	0.093265	0.121212	0.170073	0.250477	0.312756	0.277298	0.189358372
0	0	0	0	0	0	0	0	0	0
0.300074	0.289763	0.271685	0.277809	0.343939	0.290081	0.35265	0.218988	0.288295	0.314553991
0	0.011013	0.089606	0	0	0	0	0.031451	0.005499	0.001564945
0.27029	0.184329	0.271685	0.297585	0.303303	0.309582	0.219977	0.301817	0.288295	0.189358372
0	0	0	0	0	0	0	0	0	0

7) Determine the weighted sum of positive distance and weighted sum of negative distance from average solution: WSP_i and WSN_i are evaluated using Equations (10) and (11) of every website and are shown in table 1.

8) Normalize the values of WSP_i and WSN_i : Equations (12) and (13) are used to determine the $NWSP_i$ and $NWSN_i$ of every e-learning website

and are shown in table 1.

9) Calculate the appraisal score (APSi): Equation (14) is used to find the APSi of every website and are shown in table 1.

10) E-Learning Websites ranking: Finally, after evaluation of appraisal score, E-learning websites were ranked as shown in table 1.

Table 1: Ranking obtained from the WEDAS method for e-learning websites

E-Learning Websites	Websites	WSPi	WSNi	NWSPi	NWSNi	APSi	Rank
ELW1	cprogramming.com	0	0.191013	0	0.358141	0.358141	4
ELW2	cs.cf.ac.uk	0.404446	0	1	1	1	8
ELW3	programiz.com	0	0.182015	0	0.388378	0.388378	5
ELW4	geeksforgeeks.org	0.209809	0	0.518757	1	1	6
ELW5	tutorialpoint.com	0	0.297593	0	0	0	1
ELW6	fresh2refresh.com	0.022545	0.011756	0.055743	0.960496	0.960496	3
ELW7	howstuffsworks.com	0	0.265672	0	0.107264	0.107264	2
ELW8	cprogrammingexpert.com	0.311249	0	0.769568	1	1	7

METHODOLOGY VALIDATION

The W-EDAS approach is validated by comparing it to the well-known Fuzzy COPRAS method used in this work for grading and selecting E-Learning websites on dataset-I. Once the e-learning website rankings have been collected using these techniques such as W-EDAS and Fuzzy COPRAS, a test known as Spearman's rank correlation determines a correlation between the sets of ratings collected using W-EDAS and Fuzzy COPRAS. Spearman's coefficient finds the importance of interdependency between the sets of ratings or rankings. For the sake of demonstration, imagine a collection of 'n' alternatives with two separate ranking sets, R1 and R2. First, determine the ranking differences (d_i^2) between R1 and R2, and

then calculate Spearman's rank (r_s) using the equation below.

$$r_s = 1 - \frac{6 \sum d_i^2}{n(n^2 - 1)}$$

The value of (r_s) might be anything between -1 and 1. Any number closer to +1 represents a strong positive association among the two ranking sets, while any value closer to -1 represents a strong negative relationship. Furthermore, if there is a connection between the two separate sets of ranking, the strength of the association may be determined using Spearman's rank value which is shown in table 2.

Table 2: Spearman's Rank correlation results obtained between W-EDAS and Fuzzy COPRAS

E-Learning Websites	Websites	Ranking by W-EDAS	Ranking by Fuzzy COPRAS	Spearman's rank calculation of W-EDAS and Fuzzy COPRAS
ELW1	cprogramming.com	4	4	0.904762
ELW2	cs.cf.ac.uk	8	8	
ELW3	programiz.com	5	3	

ELW4	geeksforgeeks.org	6	6
ELW5	tutorialpoint.com	1	1
ELW6	fresh2refresh.com	3	5
ELW7	howstuffworks.com	2	2
ELW8	cprogrammingexpert.com.	7	7

The resulting rank correlation shows a substantial positive connection between the rankings achieved using the W-EDAS approach and those acquired using Fuzzy COPRAS.

RESULTS

According to the method and framework that is proposed, the alternative (E-learning website) with the index value having the lowest preference is number 1 which means the website is ranked or placed first, followed by increasing values with decreasing values until the website which has the

highest value is ranked or placed at last. Or we can say, the lower the reference index value, the better the ranking. Figure 2 shows the graphical depiction of the rankings of the 08 E-learning websites which are taken while applying ten ranking criteria represented from EC1- EC10. It shows that the 'tutorialpoint.com' (ELW5) website has the lowest appraisal score value, so ranked/placed at number 1, followed by 'howstuffworks.com' (ELW7) at number 2, while the E-learning website 'cs.cf.ac.uk' (ELW2) is rated as the last number (number 8) with the highest appraisal score value.

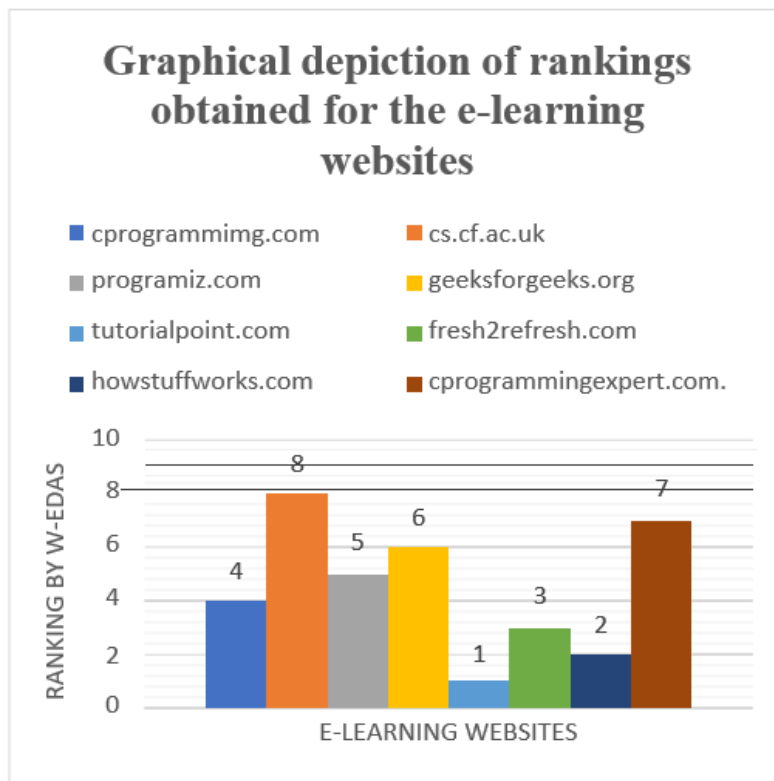


Fig 2: Graphical depiction of rankings obtained for the e-learning websites

The ranking results acquired using the W-EDAS approach are also compared to the results obtained using the existing method fuzzy COPRAS[21]. Figure 3 demonstrates the significant association

between the ranks of fuzzyCOPRAS and W-EDAS via a graphical depiction of the comparative rankings of these two techniques.

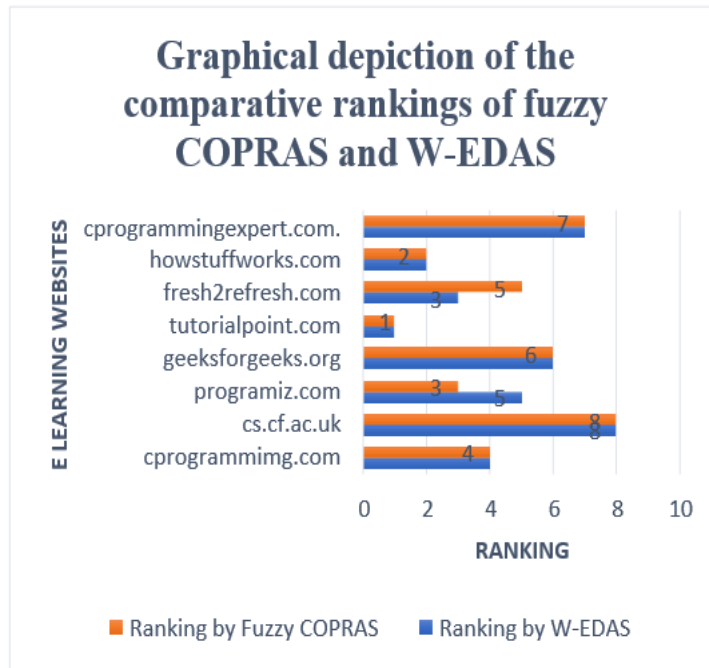


Fig 3: Graphical depiction of the comparative rankings of fuzzy COPRAS and W-EDAS

SIGNIFICANCE OF W-EDAS

Humans have grown more reliant on information technology in today's environment. The e-learning websites handle and regulate every aspect of learning. As a consequence of this dependence, websites and apps with a widerange of functions are created. Every software developer aspires to create highly dependable e-learning websites at the lowest possible cost. W-EDAS is used in this study to make the best choice of e-learning websites. Although other MCDM techniques have previously been deployed, such as TOPSIS, VIKOR, weighted criteria value, and so on, W-EDAS has significant benefits, as shown below.

- The W-EDAS has a significant advantage over other types in that it considers both positive and negative distances from the average solution. The appraisal score used to rank e-learning websites is calculated by normalizing the weighted sum of positive and negative distance matrix that directly increase ranking accuracy.
- Priority weights of performance indexes are taken into account by W-EDAS because priority weights directly impact ranking results in each MCDM scenario.
- W-EDAS is a systematic and straightforward calculation procedure that accurately represents the basic principle of real-world MCDM situations.

CONCLUSION, IMPLICATIONS, AND FUTURE SCOPE

Conclusions: This evaluation targets on the upcoming problem of evaluating, ranking, and selecting E-learning websites, having a significant impact on the educational industry. W-EDAS (Weighted Shannon Entropy approach mixed with EDAS approach) is a unique updated technique that is used for the first time to address the current issue by portraying it as an MCDM problem. To reveal the applicability and utility of the proposed W-EDAS technique in solving the current challenge of selecting E-learning websites, a case study is also included. The concept of validating the W-EDAS ranking findings by comparing them to existing MCDM systems such as fuzzy COPRAS and using Spearman's rank correlation test enriches the current study.

Implications: The main implication of this study is that it only looked at one dataset of e-learning websites. Because of its exploratory and interpretative character, this study opens up a lot of websites for further investigation, especially in terms of e-learning website evaluation and rankings.

Future Scope: New e-learning websites may be considered, various approaches such as priority weight calculation, the best-worst method can be

used, more datasets can be considered, and the sensitivity analysis ideacan be applied, among other things.

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