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"Top E-Learning Websites for Knowledge Seekers: A Comprehensive Selection Guide"

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Abstract: E-Learning Websites for Knowledge Seekers: A Comprehensive Selection Guide. Introduction: The choice of e-learning websites is essential for those looking for online education. Given the wide range of platforms accessible, considerable thought should be given to aspects like course variety, cost, interactive features, user reviews, and website repute. A wisely designed e-learning platform can open up a world of information and learning opportunities. Research Significance: The choice of e-learning websites has a big impact on research since it affects how successful and efficient online learning experiences are. Learning engagement, contentment, and academic success can all be improved by having a clear understanding of the standards for selecting dependable, user-friendly systems. This study's findings can help educators, organizations, and students choose the best e-learning platforms for their needs. Methodology: A decision-making strategy called the weighted sum method produces a weighted total to rank options according to how well they perform against various criteria. Alternative parameters: Site1, Site2, Site3, Site4, Site5, Site6 Evaluation parameters: usability, reliability, portability, personalization, learning community Result: From the results it is seen that Site 4 Stands on the top of the table by securing the 1st rank which was acquired by using WSM method. Conclusion: The first ranking is obtained by having the lowest preference score.
Keywords: E-Learning, Fuzzy Logic, WDBA, COPRAS, ranking criteria.

1. INTRODUCTION

E-learning is a term describing a contemporary method of teaching and learning that makes use of electronic media, notably the internet, as a means of disseminating information. Through the use of virtual classrooms and network-enabled tools, it departs from conventional classroom-based learning. E-learning is essentially the use of digital platforms and web-based learning tools to deliver instruction to students via digital channels including computers, CD-ROMs, the internet, and DVDs. The emphasis is on utilizing technology to streamline the delivery of education and produce engaging learning environments for students (Mahanta & Ahmed, 2012). The concept of e-learning is based on this movement towards electronic media, such as computers and the internet (Covella & Olsina Santos, 2002). [1] Information technology has had a significant impact on schooling. The teaching and learning process is being revolutionized by e-learning, a new technology created by web developers. For the purpose of knowledge acquisition, it makes use of electronic media including the internet, video/audio tapes, and intranets. E-learning refers to educational activities carried out on networked computers and other electronic devices, enabling higher education students to learn whenever and wherever they want without having to physically visit academic institutions. E-learning and remote learning are synonymous due to the flexibility and freedom to learn outside of the traditional classroom setting. [2] With its accessibility, affordability, and high-quality learning opportunities, e-learning is becoming a more popular way of instruction. Research emphasizes the significance of elements including study modules, user interface, and support in determining the effectiveness of e-learning. With the use of multimedia tools and graphical animation, e-learning platforms play a significant role in delivering interesting content. Organizations are using e-learning services more frequently, and renowned colleges provide free course materials. With the proliferation of educational websites, selecting the best platform is essential. This study suggests using the PIV approach to resolve the selection problem [3] On analyzing, choosing, and ranking e-learning websites, extensive study has been done. It has been suggested to employ a number of characteristics and criteria, including as staff support, interactivity, credibility, quality assurance, learner assistance, content quality, and user-friendliness. Different approaches have been used, including fuzzy axiomatic design, AHP, and distance-based approximation. Influential factors include ones like dependability, culture, usefulness, and support. These studies aim to enhance user happiness and e-learning results while taking into account elements like system quality, usability, stability, and accessibility. [4] This study paper suggests a novel method for assessing and choosing e-learning websites termed linguistic hesitant fuzzy TODIM (LHF-TODIM). The method makes use of linguistically hesitant fuzzy sets (LHFSs) to deal with the ambiguous assessment data that experts supply. The expanded Best-Worst Method (BWM), which uses a constrained optimization model to determine the weights of evaluation criteria, is also introduced in this study. To further rank the e-learning websites and determine which the best for network teaching is, a modified TODIM approach is offered. An actual case is used to illustrate the use of the LHF-TODIM model, and a comparison is made to show the benefits of the suggested method for evaluating e-learning websites. [5] E-learning has become a popular and economical way of education in the contemporary environment, enabling learners' flexibility and accessibility. Effective techniques of evaluation and selection are required as a result of the popularity of e-learning websites. The COPRAS, VIKOR, and WDBA multi-attribute decision-making approaches are used in this study to tackle this issue. These approaches have benefits including simplicity, adaptability in weighing selection criteria, and capacity for handling a huge number of possibilities. The study uses these techniques in an effort to offer a method for determining and choosing the best E-learning websites. [6] The growing use of E-learning websites in academic institutions today has presented students with a difficult choice: "How to select the best E-learning website?" Multiple criteria are employed to analyses and rank the options in this problem, which has been classified as a MADM problem. MADM strategies have been shown to be successful in resolving difficult real-world issues and can offer decision-makers thorough rankings of potential options. The current study emphasizes the requirement for a framework to solve the ranking issue with E-learning websites utilizing MADM methods. Even though techniques like AHP, TOPSIS, VIKOR, and WDBA have been used in this situation, they have several drawbacks including high complexity and slow execution. Academics, administrators, and others would benefit from an effective selection of e-learning websites. [7]The goal of this study was to determine the best selection criteria for e-learning websites. They came up with 45 selection criteria in total, which they divided into two primary categories: quality considerations and E-learning-specific ones. To organize these criteria, a six-level hierarchical framework was created. While the second level included the two primary criteria, the first level indicated the goal of choosing an e-learning website. Ten sub-criteria and 35 sub-sub-criteria were present in the third and fourth levels, respectively. In order to assess the relative importance of each criterion, the priority weights have to be calculated at the fifth level. The final level of the hierarchy concentrated on choosing the top e-learning website according to the established criteria. [8]Given that selecting the best website requires taking into account a number of different factors, the selection of websites is in fact a multi-attribute decision-making (MADM) problem. On the basis of their unique issues and goals, various researchers have carried out investigations in this field using various MADM techniques. For instance, the Analytic Hierarchy Process (AHP) was used in one study to choose the top website for online advertising while taking into account five different factors. AHP was utilized in another study to assess relative weights and Grey Relational Analysis (GRA) to rank alternatives when choosing internet advertising networks. In a related study, the Fuzzy Analytical Hierarchy Process (FAHP) was used to assess the quality of e-commerce websites, and the Fuzzy Set Theory and Technique to Order Preference by Similarity to Ideal Solution was used to pick mobile commerce websites.[9]Various facets of learning efficacy, performance, user experiences, and perspectives have been examined in previous e-learning studies. These research' main conclusions are as follows: Douglas and Van Der Vyver tested the effectiveness of e-learning for off-campus students by giving them access to all of the text's multiple-choice questions and answers. Performance on multiple-choice and theory questions in the final test was enhanced as a result of the strategy. In a conventional, instructor-led graduate course, Capel and Hayne looked into users' prior online learning experiences, satisfaction, perceived effectiveness, and quality of online learning units. They looked at consumers' happiness and opinions of self-paced independent study courses' efficiency. Huang and Capel assessed the effectiveness, level of pleasure, and perceived advantages of online educational games. [10]The development of information and communication technology has completely changed the way that knowledge is acquired and shared, revolutionizing the field of education. As a result of educators realizing the potential of web technology, e-learning platforms are now widely used all over the world. The issue for school administrators is still getting people to use their e-learning programmers. It's important for e-learning websites to have strong usability so that users may interact with the platform in a natural and spontaneous way. This study used Shackle's usability paradigm and created a survey questionnaire to evaluate usability attributes. The South Eastern University of Sri Lanka (SEUSL) final-year undergraduate population, which included both seasoned and novice users of e-learning websites, participated in the survey. According to the study's findings, the results were not significantly impacted by the students' level of familiarity with e-learning websites, whether they had some or none at all. The study did, however, support the importance of usability characteristics in promoting natural and spontaneous interactions with e-learning platforms. [11] There is a lot of potential for engaging and involving students on a bigger scale by integrating information and communication technology (ICT) with learning processes through online courses. For instance, using multimedia in problem-based learning to show real, challenging situations can inspire and interest students while also promoting the growth of problem-solving abilities. An and Regolith emphasize the fact that even while working on the same problem, several student groups may have distinct learning needs, interests, and problem-solving strategies. By enabling numerous forms of interactions, such as student-content, student-student, student-lecturer, and student-interface interactions, e-learning courses can meet these varying needs. These interactive components increase student participation in the learning process and make it more interesting. Studies have shown that online education can be just as beneficial as traditional modes of education, and in some cases even more so. According to Starves and Herder, it is essential to comprehend the demands of potential students while developing effective e-learning courses. Future users' needs can be effectively met by e-learning courses by identifying them and addressing them, resulting in a good learning experience. Furthermore, it's critical to recognize that e-learning programmers have opened up access to quality education for those who might not have otherwise had it. Participants who may have encountered obstacles to education in other situations now have access to education thanks to e-learning. Overall, e-learning programmers have the potential to be participatory and interesting learning experiences that can be tailored to the needs of different students and give them access to a high-quality education.[12]E-learning, sometimes referred to as computer-assisted learning, Web-based learning, distributed learning, online learning, or Internet-based learning, refers to a number of ways that technology is used to deliver education. Computer-assisted learning and distance learning are the two primary types of e-learning. Using computers to deliver stand-alone multimedia packages for teaching and learning is known as computer-assisted instruction. Individual learning experiences are often the main focus of this method, which also makes use of multimedia resources to improve the teaching material On the other side, distance learning uses digital technology to give education to students who are spread out geographically. It enables students to access learning resources and take part in sessions remotely, typically from a central location. Teleconferencing, chat rooms, discussion boards, and instant messaging services like Microsoft MSN, Yahoo Messenger, and Skype are just a few of the communication tools that can be included into distance learning. Academics now use e-learning extensively, so there is a rising demand for formalized rules to help instructors create, manage, and maintain their e-learning programmers. The quality of the information may vary due to the large range of e-learning systems that are offered on the market. While there is some fantastic video available, there is also a sizable amount of subpar content. To better serve the needs of content creators, educators, and students, it is necessary to fix the gaps in current e-learning services. In conclusion, e-learning includes a variety of methods and strategies for teaching while utilizing technology. Although e-learning has become more popular in academia, it still needs standardized norms and needs its service and content shortcomings to be filled.[13]

2. MATERIALS & METHODS

Selection of E-Learning Websites: e-learning websites that provide high-quality, accurate, and up-to-date content. The courses, lessons, and materials should be well-researched, professionally presented, and aligned with your learning objectives. Variety of Courses: Choose e-learning platforms that offer a wide range of courses and topics. This ensures that you have access to diverse learning opportunities and can find courses that match your interests and learning needs.

Usability: User-Friendliness: Usability is closely related to the concept of user-friendliness. A system or product is considered usable when it is intuitive and easy for users to interact with. It should require minimal effort for users to understand its functionality and accomplish their tasks efficiently. Efficiency: Usability plays a crucial role in improving efficiency. A usable system enables users to complete tasks quickly and accurately, without unnecessary delays or errors. Well-designed interfaces, clear navigation, and streamlined workflows contribute to increased productivity and user satisfaction.

Reliability: Consistency: Reliability refers to the consistent performance of a system or product over time. A reliable system delivers consistent results and behavior, without unexpected or unpredictable variations. Users can depend on the system to perform reliably under different conditions and usage scenarios. Availability: Reliability also relates to the availability of a system. A reliable system is accessible and operational when users need it. It minimizes downtime, system failures, and interruptions, ensuring that users can rely on it to be consistently available and accessible.

Portability: Platform Independence: Portability refers to the ability of a system or software to run on different platforms or operating systems without requiring significant modifications. A portable system can be easily deployed and executed on various hardware or software environments, ensuring compatibility and flexibility for users. Code Reusability: Portability often involves designing and developing software components in a modular and reusable manner. By separating platform-specific code from the core functionality, developers can create portable code that can be easily adapted and reused across different platforms. This approach saves time and effort in developing and maintaining separate codebases for each platform.

Personalization: Customized User Experience: Personalization allows tailoring the user experience to individual preferences, needs, and characteristics. By collecting and analyzing user data, such as browsing behavior, purchase history, or demographic information, personalized systems can deliver content, recommendations, and services that align with the user's specific interests and preferences. Adaptive Interfaces: Personalization enables the adaptation of user interfaces based on user profiles and contextual information. Interfaces can be dynamically adjusted to suit the user's language, accessibility requirements, device capabilities, or interaction preferences. This enhances usability and improves the overall user experience by providing a more intuitive and relevant interface.

Learning community: Knowledge Sharing: Learning communities provide a platform for individuals to share their knowledge, expertise, and experiences with others. Members can contribute valuable insights, resources, and perspectives, creating a collaborative environment where learning is enriched through the collective wisdom of the community. Peer Support and Collaboration: Learning communities foster peer-to-peer support and collaboration among members. Individuals can seek help, guidance, and feedback from their peers, creating a supportive network that enhances learning outcomes. Collaborative projects and group activities can also be facilitated within the community, promoting teamwork and cooperation.

3. WEIGHTED SUM METHOD (WSM)

An approach that is frequently used to solve multi-objective optimization issues is the weighted sum method. Although it has been used extensively in many different sectors, the literature frequently concentrates on the application itself rather than analyzing the method in detail or taking preferences into account. The weighted sum approach has many applications, although they are typically restricted to issues with just two objective functions. By methodically altering the weights, Koski and Silvennoinen (1987) used the weighted sum approach to create several Pareto optimum solutions. Their use involved reducing a four-bar space truss's volume and nodal displacement. The technique was also applied by Kassaimah et al. (1995) to the two-objective optimization of laminated plates. They sought to reduce deflection while increasing the critical buckling shear stress. Although several weighting schemes were taken into account, and the associated solutions were contrasted, the method itself and the expression of preferences were not completely investigated. The weighted sum approach was used by Proos et al. (2001) to optimize the topology in two-dimensional planar stress situations. They sought to increase the natural frequency's first mode while minimizing compliance. To accurately depict the Pareto ideal set, the weights were changed. A weighted sum was used by Saramago and Steffen (1998) in their optimization-based method to combine two objective functions and forecast robotic motion. They were irrelevant to the decision-making process because the weights in their case had the same value. In conclusion, the weighted sum approach has been widely applied in multi-objective optimization, although research on the method itself or the expression of preferences has not received as much attention. The supplied examples demonstrate its use in a variety of optimization problems with two objective functions, but additional study is required to see whether it can be applied to more challenging issues and take preferences into account.[1]The method for bi-objective optimization that is effectively introduced in this paper establishes a Pareto front and can be expanded to cover multiple objectives. Traditional weighted-sum techniques, which are frequently employed in multiobjective optimization, have drawbacks include creating solutions that are unevenly distributed along the Pareto front and failing to identify solutions in non convex regions. By adaptively altering the weights among the objective functions to concentrate on uncharted territory, the suggested method, known as the adaptive weighted sum method, addresses these limitations. This method dynamically modifies the weights while the optimization process is taking place, in contrast to the conventional approach, which depends on a priori weight selections. In order to direct the search towards promising areas, it also contains extra inequality constraints. By contrasting the adaptive weighted sum method with alternative approaches in two numerical examples and a straightforward structural optimization issue, the study illustrates the usefulness of this approach. The findings demonstrate that the suggested strategy effectively neglects non-Pareto optimal solutions while producing well-distributed solutions along the Pareto front and identifying Pareto optimal solutions even in nonconvex regions. The use of equality constraints in the Normal Boundary Intersection approach, which results in the inclusion of non-Pareto optimum solutions, is also highlighted as a potential weakness in the research. The proposed approach incorporates inequality constraints to get around this restriction. Overall, the research introduces a reliable bi-objective optimization methodology that outperforms more established techniques. The exhibited results confirm that the proposed adaptive weighted sum technique is efficient in locating well-distributed Pareto optimal solutions, including those in non convex regions, while ignoring non-Pareto optimal solutions.[2]When there is only one criterion to be optimized, single-dimensional issues are frequently solved using the Weighted Sum approach. By calculating the weighted sum of the criterion values for each alternative, the best alternative can be identified in these situations. The Weighted Sum approach, for instance, determines each alternative's score as the product of its actual values for each criterion and the accompanying weights when there are m alternatives and n criteria. The option that maximizes this score is the ideal one. It is more difficult to use the Weighted Sum approach for multi-dimensional decision-making, though. In certain situations, it may be difficult to directly combine distinct dimensions using the additive utility assumption since they may have different units. According to the additive utility assumption, it is possible to add the values of many criteria to determine the overall utility or worth of a certain choice. It may not be suitable to simply add the criteria together when they have different measurement scales or units. As a result, different strategies that take into account the variations in measurement scales and units, such multi-criteria decision analysis (MCDA) methodologies, are frequently utilized in multi-dimensional decision-making situations. To give a more thorough evaluation and ranking of alternatives, these methods take into account the relative relevance of criteria, the trade-offs between them, and the many scales or units in which they are assessed. In conclusion, while the Weighted Sum method is a simple strategy for one-dimensional problems, it might not be appropriate for multi-dimensional problems when various criteria have various scales or units. Such situations should be addressed by more sophisticated techniques like MCDA.[3]The weighted sum method is typically used in the first stage of the strategy described to identify the general shape of the convex regions of the Pareto front. The weighted sum approach involves sequentially getting Pareto optimum solutions by adjusting the weights given to the objective functions. However, during this phase, the conventional weighted sum approach might not be able to detect non convex portions of the Pareto front. The Pareto front's non convex zones are identified and taken into consideration in later optimizations. The patches that need additional refinement are chosen based on the size or importance of the patches that make up the Pareto front. The areas of interest for obtaining a more precise depiction of the Pareto front are these chosen patches. More equality constraints are added to speed up the refinement process. By limiting the optimization process to the chosen patches, these limitations enable more targeted sub optimization within these areas. By doing this, the strategy tries to hone and enhance the Pareto front representation, especially in non convex regions that were missed in the preliminary stage using the weighted sum method. This two-stage method, in general, combines the initial exploration of the convex regions using the weighted sum method with the refinement and identification of the non convex regions using selective optimization and the insertion of extra equality constraints. The goal of this strategy is to produce a more precise and thorough depiction of the Pareto front.[4]By giving weights to each objective function, the weighted sum approach for multi-criteria optimization reduces the issue to a single-objective optimization. Each objective function's relevance Qi(x), where x stands for the decision variables, is reflected in the choice of weighting coefficients, denoted as i. Finding the choice variables' ideal values to maximize or minimize the weighted sum of the objective functions is the goal. The weighted sum approach has various restrictions and downsides while being widely used and simple to use. One of the challenges is that the Pareto optimal set may not always be accurately and completely represented by merely continually altering the weights. Instead of capturing the whole set of Pareto optimal solutions, the weighted sum technique have a tendency to concentrate on a single point on the Pareto front. Furthermore, as noted in the reference [5] (not specified in the current context), minimizing the weighted sums of objectives in multi-criteria optimization issues can have some drawbacks. The failure to accurately capture trade-offs between competing objectives, the absence of sensitivity analysis, or the potential loss of significant Pareto improvements are a few examples of these downsides. It is significant to remember that, despite the weighted sum method's popularity and widespread use in multi-criteria optimization, it may not always provide a complete and accurate representation of the Pareto optimal set, necessitating the use of additional techniques or improvements to address its shortcomings. [5] A well-known and frequently discussed idea in multi-objective optimization is the weighted sum technique. Since its introduction by Zadie [53], it has received significant attention in the literature. Using a weight vector, the method entails linearly combining each of the distinct goal functions of a multi-objective problem (MOP) into a single objective. The weighted sum approach was mostly applied in an a priori and interactive manner prior to the popularity of evolutionary multi-objective (EMO) algorithms. A weight vector is predefined before the search in the a priori technique, but weights are gradually adjusted in the interactive approach. These methods enabled the investigation of many Pareto optimum solutions. The weighted sum approach, for instance, is used to optimize multi-objective structures in [54], where weights are pre-defined and several Pareto optimal solutions are produced by methodically altering the weights during many algorithm runs. Similar to [55], weights are changed in the weighted sum approach for topology optimization to produce various Pareto optimum solutions. In EMO algorithms, the weighted sum approach is used to search for a number of Pareto optimal solutions in a single run. This method is embedded with a set of pre-defined weights. An example of a multi-objective genetic algorithm that uses the weighted sum approach with random weights is used in [56] to find effective solutions. The weighted sum approach, with evenly distributed weights, is applied in the MSOPS [57] and MOEA/D [17] algorithms. Overall, both independently and as a component of EMO algorithms, the weighted sum method has been widely applied in multi-objective optimization. It provides a flexible method for investigating and obtaining a variety of Pareto optimal answers to multi-objective optimization issues. [6] Black box simulation multiobjective optimization is dealt with by the suggested method, PAWS (Pareto front Approximation with an Adaptive Weighted Sum method). PAWS is an iterative technique that employs a trust region approach and a metamodeling framework to enhance a group of non-dominated points towards the Pareto front. Based on the given data, a met model is built for each individual objective function in PAWS for each iteration. The sampling region for the met models is chosen using the trust region approach, which was developed as a result of Conn et al.'s (2000) research. This facilitates efficiently navigating the objective space. The next step is to look for Pareto optimum sites using the weighted sum approach. The weight combination in the weighted sum technique is determined adaptively, which distinguishes PAWS from other systems. It incorporates every existing non-dominated point, enabling a more thorough and efficient search for the Pareto front. The study's numerical findings show that PAWS has the ability to uniformly cover the Pareto front even when the Pareto front is nonconvex. This shows that PAWS is a potential approach for dealing with multiobjective black box simulation optimization problems and achieving a wide range of evenly distributed Pareto solutions. Overall, PAWS improves the search for the Pareto front in a black box simulation multiobjective optimization context by combining metamodeling, trust region approaches, and adaptive weighting.[7]For analyzing mutations in genetic investigations, the proposed method introduces a weighted-sum methodology. A weighted total of the mutation counts is used to evaluate each individual after the mutations are categorized according to their function, such as by gene. The objective is to determine whether affected people have more mutations than unaffected people. Permutation is used to take into account the weighting of mutations and the requirement of seeing a mutation in order to incorporate it in the study. Permutation includes randomly switching the disease state between those who are afflicted and those who are not, allowing the statistical analysis to be adjusted. Importantly, even in the presence of linkage disequilibrium (LD), a measurement of the non-random relationship between genetic variations, permutation preserves the proper type I error rate. By weighing variations differently when determining an individual's genetic load, the weighted-sum technique varies from the CAST (Combined Annotation-Dependent Depletion) method. The technique avoids being excessively influenced by common mutations by assigning more weight to unusual mutations in unaffected individuals. In contrast, if several common mutations are present in a group, the CAST technique may be dominated by their influence, resulting in the existence of many mutations in practically all individuals. The CAST approach may make use of frequency thresholds, as suggested by the CMC (Combined Multivariate and Collapsing) method, to lessen the impact of frequent variants. The choice of thresholds can impact the test findings, and choosing biologically appropriate thresholds might be difficult. All mutations are included in the weighted-sum technique, but their weights are depending on how frequently they occur in people who are not affected. This method eliminates the requirement for frequency criteria, allowing for a more flexible analysis. In conclusion, the suggested weighted-sum method organises mutations by function and uses a weighted sum methodology to analyse mutations in genetic investigations. To account for weighting and the requirement of seeing mutations, permutation is used. The strategy prevents the dominance of common variants seen in other approaches by placing an emphasis on rare mutations in unaffected individuals. Additionally, it doesn't reliant on frequency thresholds, giving the analysis flexibility. [8]The non-uniform distribution of optimal solutions and the inability to find optimal solutions in non-convex regions are the weighted sum method's two fundamental flaws. The adaptive weighted sum (AWS) method, which adds extra inequality constraints to direct the optimisation process towards undiscovered regions, was created by the authors of the research to solve these shortcomings. The AWS technique gets around these issues by adding a new viable zone that is bounded by additional inequality constraints and calls for more investigation. This strategy enables a more thorough look for the best answers. By generating well-distributed answers, locating Pareto optimal solutions even in non-convex regions, and ignoring non-Pareto optimal solutions, the AWS technique has proven to be successful in addressing bi-objective optimisation problems. It is crucial to remember that the AWS method's earlier iteration was created especially for bi-objective optimisation issues. The authors' goal in this study is to broaden the applicability of the methodology to issues with more than two objectives by presenting a generalised multiobjective adaptive weighted sum method. This distinction is used to set the new method suggested in the paper apart from the original bi-objective method.Overall, by including additional inequality constraints, improving solution space exploration, and offering a more thorough method for multiobjective optimisation, the generalised multiobjective adaptive weighted sum method addresses the drawbacks of the conventional weighted sum method.[9]It's challenging to understand the context and the precise links between the assertions in the passage you provided because it seems to cover a wide range of subjects in numerous fields. It refers to the application of analytical methods to establish interference parameters in a diode version for solar modules, the consideration of multi-cell downlink systems in MISO (Multi-Input Single-Output) systems with the Weighted Sum-Rate Maximisation problem, and the suggestion of a solution based on a branch and bound strategy. Additionally, it discusses the usage of the Weighted Sum approach for ranking, the design of transceivers using the weighted MMSE (Minimum Mean Square Error) approach, and the evaluation of characteristic curves A1, A2, A3, and A4 based on irradiance, temperature, current, and voltage parameters. It's difficult to offer a thorough justification or insightful observations in the absence of additional background or targeted inquiries. Please let me know if you have any specific queries or require clarification on a certain topic, and I'll be pleased to help.[10]In the excerpt you gave, the Weighted Sum Method (WSM) is emphasised as a well-liked and frequently applied subjective multi-criteria decision-making technique. It is derived from Multiple Attribute Decision Making (MADM) techniques including Simple Additive Weighting (SAW), Factor Rating, and Simple Scoring Method. The WSM is renowned for its applicability and simplicity, making it usable by practitioners with little or no background in mathematics. Each choice receives a score in the WSM depending on pertinent factors, with each criterion weighted in accordance with its significance. The process entails calculating the highest scores for each criterion, taking into account various levels of each criterion, and allocating suitable scores for each level. The WSM simplifies the process of shortlisting or screening criteria and permits the mixing and connecting of data to generate recommendations or rankings by taking into account the traits, values, and needs associated with each component. The WSM offers a structured method for decision-making by methodically assessing options according to a number of criteria and their relative weights.[11]When using the Weighted Sum Method (WSM), each alternative's value is calculated by adding the attribute values times the corresponding weights. Several research have used this strategy [19, 20]. The weights assigned to each selection criterion are taken into consideration before computing the weighted total in the WSM, where each alternative is assessed based on its scores for each selection criterion.The WSM has drawn criticism for a few drawbacks, though. One criticism of the method is that attribute weights are not clearly defined and that different types of information are added without a clear methodology for doing so. The results may be skewed due to the lack of a systematic weight determination process, which introduces subjectivity. Another complaint is that the WSM might ignore the connections or dependencies between characteristics. Because the technique does not explicitly capture the information about dependencies between qualities, it may result in the loss of crucial knowledge or relationships between criteria.Due to its simplicity and ease of use, the WSM is still a well-liked and useful method for multi-criteria decision making despite these shortcomings. When using the WSM in decision-making situations, researchers and practitioners should be aware of these limitations and take them into account.[12]The significance of the linear weighted sum approach in establishing the best carbonation conditions for strengthening the characteristics of recycled concrete aggregates (RCA) is highlighted in this work, which is significant. The researchers were able to reduce processing time significantly by using this strategy to determine the ideal pretreatment and carbonation times. This discovery offers a more effective and expedient method, which has significant potential for the building industry. The study also demonstrated how Ca-rich effluent from ready-mixed concrete batching plants can be used in real-world applications. This effluent turned out to be helpful in enhancing the characteristics of RCA. This emphasises the significance of environmentally friendly practises in the building industry, where waste materials can be recycled to improve the quality of aggregates.The study also showed relationships between the mechanical and durability characteristics of concrete built with standard coarse aggregates and carbonated RCA. This knowledge aids in the development of more durable and sustainable construction techniques by offering useful insights into the performance of concrete made using recycled resources. This work adds to the corpus of knowledge on waste utilisation, improving carbonation conditions, and comprehending the characteristics of concrete made using recycled aggregates. The research has applications in the construction sector, with possible advantages in terms of productivity, sustainability, and concrete quality.[13]

4. RESULT AND DISCUSSION

TABLE 1: Selection of E-Learning websites

Selection of E-learning websites					
	usability	reliability	portability	personalization	learning community
Site1	3.20	4.06	4.26	4.06	4.26
Site2	7.40	7.20	7.80	8.40	8.20
Site3	5.80	5.40	6.20	4.20	5.20
Site4	8.87	8.40	8.87	7.80	8.87
Site5	6.40	5.80	7.60	6.60	6.40
Site6	8.60	8.53	8.87	8.33	8.00

Table 1 shows the Selection of E-Learning Websites using the Analysis Method Alternative: Site1, Site2, Site3, Site4, Site5, Site6 and Evaluation parameters: usability, reliability, portability, personalization, learning community.

FIGURE 1. Selection of E-Learning Websites

Figure 1 shows the Selection of E-Learning Websites using the Analysis Method the usability has the Highest value in site 4 and lowest value in site 1. The reliability has the Highest value in site 5 and lowest value in site 1. The portability has the Highest value in both site 3 and site 5 and lowest value in site 1. The personalization has the Highest value in site 2 and lowest value in site 1 and The learning community has the Highest value in site 4 and lowest value in site site 1.

TABLE 2: Normalized Data

NORMALIZED DATA					
	usability	reliability	portability	personalization	learning community
Site1	0.360767	0.4759672	0.48027057	0.483333333	0.480270575
Site2	0.834273	0.8440797	0.87936866	1	0.924464487
Site3	0.65389	0.6330598	0.69898534	0.5	0.586245772
Site4	1	0.9847597	1	0.928571429	1
Site5	0.721533	0.6799531	0.85682074	0.785714286	0.721533258
Site6	0.96956	1	1	0.991666667	0.901916573

Table 2 shows the Normalized Data for Alternative: Site1, Site2, Site3, Site4, Site5, Site6 and Evaluation parameters: usability, reliability, portability, personalization, learning community.

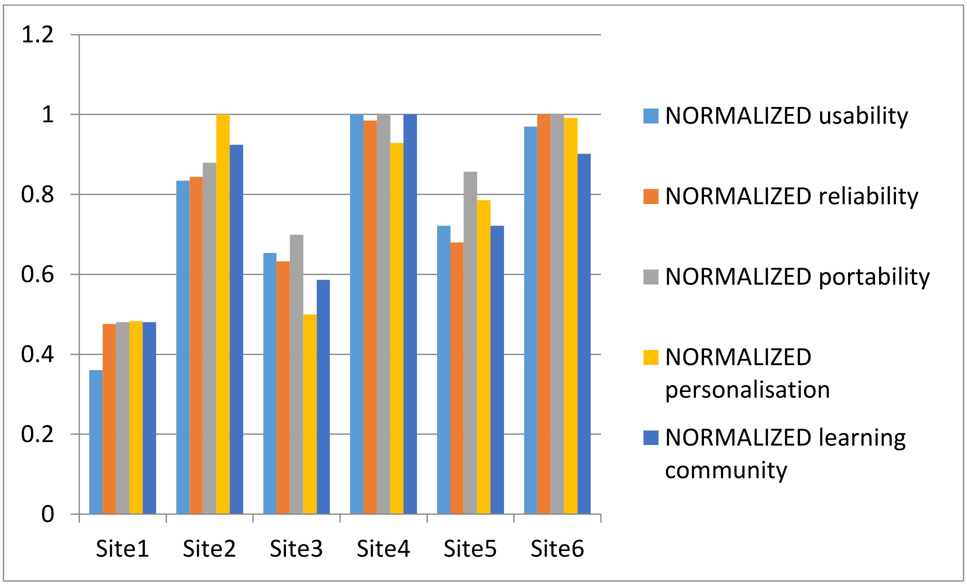

FIGURE 2. Normalized Data

Figure 2 shows the Normalized Data for Selection of e-learning websites Alternative: Site1, Site2, Site3, Site4, Site5, Site6 and Evaluation parameters: usability, reliability, portability, personalization, learning community. It is also the Maximum in Normalized Value

TABLE 3. Weightages

Weightages					
	usability	reliability	portability	personalization	learning community
Site1	0.2	0.2	0.2	0.2	0.2
Site2	0.2	0.2	0.2	0.2	0.2
Site3	0.2	0.2	0.2	0.2	0.2
Site4	0.2	0.2	0.2	0.2	0.2
Site5	0.2	0.2	0.2	0.2	0.2
Site6	0.2	0.2	0.2	0.2	0.2

Table 3 shows Weight ages used for the analysis we take same weights for all the parameters for the analysis

TABLE 4. Weighted normalized decision matrix

Weighted normalized decision matrix					
	usability	reliability	portability	personalization	learning community
Site1	0.072153	0.09519343	0.09605411	0.096666667	0.096054115
Site2	0.166855	0.16881594	0.17587373	0.2	0.184892897
Site3	0.130778	0.12661196	0.13979707	0.1	0.117249154
Site4	0.2	0.19695193	0.2	0.185714286	0.2
Site5	0.144307	0.13599062	0.17136415	0.157142857	0.144306652
Site6	0.193912	0.2	0.2	0.198333333	0.180383315

Table 4 shows weighted normalized decision matrix using the Analysis Method Alternative: Site1, Site2, Site3, Site4, Site5, Site6 and Evaluation parameters: usability, reliability, portability, personalization, learning community.

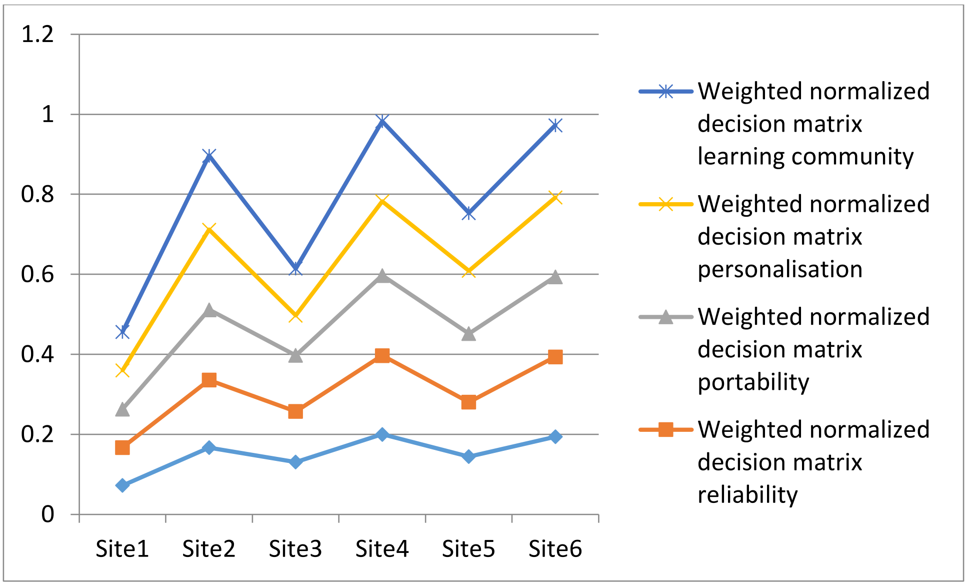

FIGURE 3. Weighted Normalized Decision matrix

Figure 3 shows the weighted normalized decision matrix Analysis Method Alternative: Site1, Site2, Site3, Site4, Site5, Site6 and Evaluation parameters: usability, reliability, portability, personalization, learning, communication.

TABLE 5. Preference Score & Rank

	Preference Score	Rank
Site1	0.456121657	6
Site2	0.896437139	3
Site3	0.614436084	5
Site4	0.98266622	1
Site5	0.753110931	4
Site6	0.972628711	2

Table 5 shows the final rank of this paper the Site 1 in 6th Rank, The Site 2 in 3rd Rank, The Site 3 in 5th Rank, The Site 4 in 1st Rank, The Site 5 in 4th Rank and The Site 6 in 2nd Rank. The final result is done by using the WSM method.

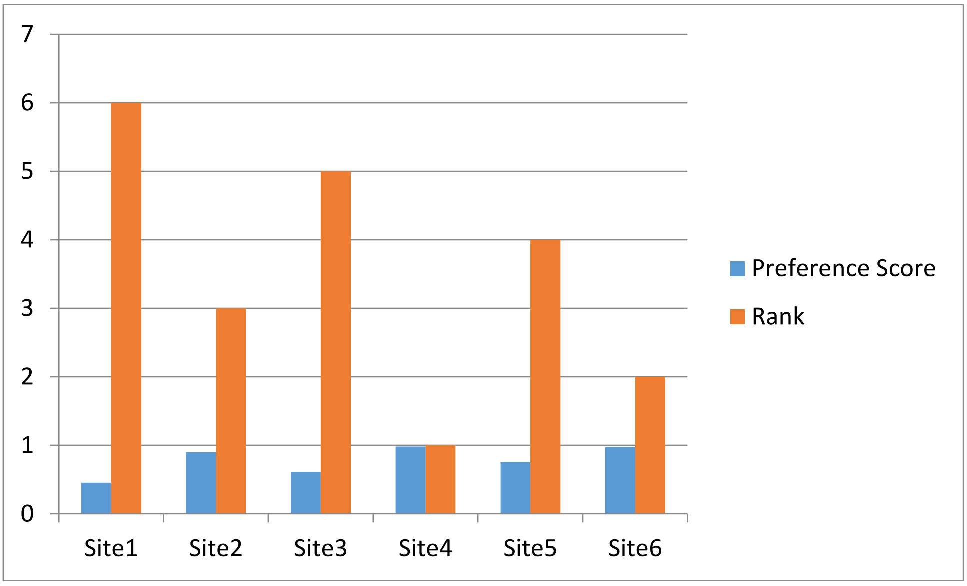

FIGURE 4. Preference Score & Rank

FIGURE 4 shows the preference score and rank on the basis of my analysis and the result is obtained by using the WSM method Site 4 stands on the top by securing 1st position on the table.

5. CONCLUSION

In today's digital age, the selection of e-learning websites has become paramount for individuals seeking quality online education. With a plethora of platforms available, it is crucial to carefully evaluate and choose the right website that aligns with one's learning goals and preferences. The process of selecting an e-learning website involves considering various factors such as course variety, affordability, interactive features, user reviews, and the reputation of the platform. Firstly, the range and diversity of courses offered by an e-learning website play a significant role in its appeal. A well-rounded platform should provide a wide selection of courses spanning various disciplines and skill levels. Whether someone is interested in language learning, computer programming, or business management, having access to a diverse catalog ensures the ability to pursue individual interests and goals. Affordability is another crucial consideration. While some e-learning websites offer free courses or have affordable subscription plans, others may have higher price points. Evaluating the cost-to-value ratio is important to ensure that the chosen platform provides high-quality educational content that justifies the investment. Interactive features greatly enhance the e-learning experience. Features like video lectures, quizzes, assignments, discussion forums, and interactive simulations facilitate active learning and learner engagement. The presence of such interactive elements not only fosters deeper understanding but also provides opportunities for practical application and collaboration with fellow learners. User reviews and testimonials can serve as valuable insights into the effectiveness and credibility of an e-learning website. Reading reviews and feedback from current or previous users can offer a glimpse into the user experience, course quality, and overall satisfaction. Platforms with positive feedback and a strong community of learners are more likely to provide a rewarding educational journey. Lastly, the reputation of an e-learning website should be considered. Established and well-known platforms often have a track record of delivering high-quality content, experienced instructors, and reliable technological infrastructure. Researching the background, track record, and credibility of the platform can help ensure a reliable and reputable learning experience. In conclusion, the selection of an e-learning website is a critical step towards accessing quality online education. By carefully considering factors such as course variety, affordability, interactive features, user reviews, and reputation, individuals can make informed decisions that align with their learning objectives and preferences. Choosing the right e-learning website opens doors to a world of knowledge, personal growth, and skill development in the digital learning landscape. With the right platform, individuals can embark on a fulfilling educational journey and unlock their full potential.

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