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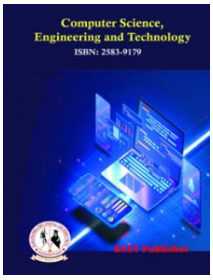

Assessing the Effectiveness of Computer-Aided Learning (CAL) Platforms using Fuzzy TOPSIS Method

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Abstract: *Computer-aided learning (CAL) is an innovative educational approach that leverages technology to enhance the learning experience. It involves the integration of computers and software applications into traditional teaching methods, allowing students to interact with digital content, simulations, and multimedia resources. CAL provides personalized and self-paced learning opportunities, catering to diverse learning styles and needs. The use of computers as educational tools can foster student engagement, critical thinking, and problem-solving skills. As technology continues to advance, computer-aided learning continues to evolve, revolutionizing the way education is delivered and accessed in classrooms and beyond. Computer-aided learning (CAL) holds significant research importance due to its potential to transform education and enhance learning outcomes. The research on CAL explores its effectiveness in various educational settings, subjects, and age groups. Understanding how technology integration impacts student engagement, motivation, and knowledge retention is crucial for educators and policymakers. CAL research also delves into the development and evaluation of interactive learning materials, adaptive learning algorithms, and virtual simulations. Investigating the role of CAL in promoting self-directed learning and critical thinking skills is of particular interest. Additionally, CAL research addresses equity and accessibility issues, examining how technology can bridge the educational gap for marginalized or underserved populations. Evaluating the cost-effectiveness and scalability of CAL implementation is vital for institutions and governments planning to adopt such systems. Fuzzy TOPSIS is a decision-making technique used in various fields to handle ambiguity and uncertainty. It ranks alternatives based on their distance from the positive ideal solution and the negative ideal solution. This approach has been successfully applied in practical challenges across industries, such as resources, business, and healthcare. Fuzzy TOPSIS utilizes fuzzy sets and non-hesitant fuzzy sets, combining them with TOPSIS to provide effective solutions. Its simplicity, programmability, and ability to consider different criteria with varying units make it a valuable tool for decision-making processes. Recent developments in obscure TOPSIS techniques incorporating ambiguous numbers have further improved its capabilities. Alternative taken as Course Variety, User Reviews, Price Range, Customer Support. Evaluation Parameter taken as Khan Academy, Coursera, Udemy, edX, Codecademy. The result it is seen that Udemy is got the first rank where as is the edX is having the lowest rank.*

Keywords: *Khan Academy, Coursera, Fuzzy TOPSIS.*

1. INTRODUCTION

Computer-aided learning (CAL), also referred to as Computer Assisted Instruction, Computer-Assisted Instruction, and Computer-Based Instruction, involves instructional methods that use digital files to provide text, visuals, and sounds in a multimedia approach to learning. A meta-analysis conducted by Kulik and Kulik, which reviewed 254 controlled studies evaluating computer-based instruction, showed that students using these programs achieved 0.3 standard deviations higher scores on average, leading to positive changes in attitudes and reduced instruction time. In the context of dental education, a consolidation of 34 comparative studies found that CAL, when compared to conventional teaching methods, yielded small to moderate positive effects on academic achievement. However, another review by Rosenberg et al. reported no significant difference in test scores between CAL and traditional teaching methods. [1] CAL has been recognized as a self-instructional tool that can motivate students to learn and offers a flexible mode of delivery. It can be particularly applicable in orthodontics, although its use in this field is currently limited to a few undergraduate and postgraduate teaching institutions. Some commercially available CAL packages, such as those outlined by Byrne and Lowe, are designed to facilitate orthodontic education and may be explored further. The availability of CAL resources has expanded with the advent of the internet, making it easier to access and discuss various computer-based CAL plans.[2] Computer-aided learning (CAL) can be particularly beneficial in educational settings for students with autism or related subtypes, such as Asperger's Syndrome. These students may have unique attributes, such as a keen interest in specific subjects or topics. The CAL system is designed to cater to their needs, making the learning experience more engaging and inspiring, which can lead to a deeper understanding of the subject matter. Researchers like Attwood (1998) and Jordan (1991a; b; 1992a; b) have explored the potential benefits of CAL for autistic students, highlighting how it addresses the challenges they may face in traditional educational settings. CAL can play a valuable role in accommodating these difficulties and has the potential to address a wide range of complications associated with autism.[3] In national educational settings, CAL can be integrated into the curriculum to support students with autism, and it is considered a practical and valuable tool in special needs education. Such software can be adapted to cater to the specific requirements of autistic students, offering a personalized and effective learning experience. CAL's main application in catering to the needs of autistic students is evident, and it is considered a valuable resource to help them find their appropriate learning niche. By tailoring educational approaches to their individual needs, CAL can help autistic students thrive in their academic journey.[4] Computerized learning has tremendous potential to significantly improve students' learning experiences by serving as a valuable supplement to traditional teaching methods or as a stand-alone innovative approach. However, this potential poses a challenge to educators who must not only integrate Computer-aided learning (CAL) into the syllabus but also assess its actual impact on real learning outcomes, especially in the realm of Medical Education. [5] The rapid adoption of Computer-aided learning (CAL) in classrooms is driven by the desire to enhance education in various regions. CAL serves as an effective assistant to teachers, especially in technologically backward areas where efforts are made to introduce children to computers despite limited resources and funding from State Education Funds, international agencies, and private groups. In the development of CAL, communication among children is emphasized, and self-directed learning is encouraged. The use of CAL is not limited to a specific curriculum; instead, it offers diverse applications and modules for children of different ages, ranging from 5-year-olds to high school students. [6] In India, CAL has been successfully used for primary school children through observational learning modules and diagnostic classroom activities, showing promising results when children control the computer and share resources. In multi-user environments, some children excel, particularly those who are adept at mouse control. Research suggests that learning software primarily designed for single-users can be resourceful in regions where resources are limited, but a strong case is presented for developing multi-user CAL software to further enrich the learning environment for children with unique learning styles. [7] Computer-aided learning (CAL) in the context of accounting differs from traditional studies, as it involves using CAL for teaching non-specialized accounting topics to students. Questionnaire data were collected both at the beginning and end of the course, and statistical analysis was conducted to examine its impact on student performance. [8] The analysis shows that age and approach to accounting did not significantly influence the outcomes, but CAL seems to have some influence on students' entry qualifications. Students who used CAL appeared to be negatively affected in their understanding of accounting concepts. Research indicates that CAL is easy to use and students are more likely to find it helpful, but there is still a chance for some students to face challenges due to lack of computer literacy.[9] Accounting students' views on the subject became more negative after using CAL, and they were less likely to choose accounting as their area of study upon completing the course. The negative impact on students' feelings and attitudes suggests that the effective use of CAL should be carefully considered by higher learning institutions, given the limited workforce and resources.[10] CAL courses provide students with the opportunity to work on their own, allowing them to progress at their preferred pace, whether in a classroom or a library setting. They are highly beneficial for teaching various subjects like neuroanatomy due to their visually rich content, which enables students to understand complex structures and their connections in the brain. [11] CAL courses come in diverse forms, and online resources play a vital role in their implementation. They are not a separate entity but, on the contrary, integrate various techniques and methods. These courses can present information in different formats, ranging from simple text to fully interactive sites. [12] Evaluating each CAL resource is essential to determine its specific suitability for the educational goals of individual universities or coursework. The evaluation process involves assessing the techniques and methods used and whether they effectively fulfill the desired educational objectives.[13] Computer-aided learning (CAL) in dentistry has gained popularity and has become increasingly prevalent in North American dental schools, with about 25% of schools making laptops and CAL programs compulsory for students. CAL is no longer seen as just a new learning method but rather a necessary tool in the education arsenal. A well-designed CAL program can be as useful as any other learning method and offers various possibilities to add value and benefits based on the modules and accessibility to students. It allows students to learn at their own pace, review lessons, and practice conveniently, even outside the classroom environment. [14] In the field of orthodontics, a formal review concludes that there is not sufficient evidence to support CAL programs as a complete replacement for regular teaching, but they can effectively support and supplement traditional teaching methods. CAL has positive effects on student motivation and engagement in the orthodontic curriculum, especially in areas where there is a lack of teachers and resources, helping to overcome these challenges effectively. [15] Computer Assisted Learning (CAL) has gained significant importance in various engineering education departments, leading to the creation of numerous computer packages designed to aid learning. Among these, powerful CAL packages based on the World Wide Web (WWW) or the Internet have emerged as the latest trend. The internet provides an improved educational environment, offering interactive self-paced learning suitable for distance education. [16] The internet serves as a versatile tool for education, allowing access to vast amounts of information, delivering complete courses, and providing lessons for classroom teaching. It serves three key functions, making it a fascinating resource in the present time. Internet-based CAL tools offer several advantages over traditional methods, including simplicity, accessibility from anywhere in the world at any time, direct communication between developers and users, and the potential for continuous content updates that directly benefit users and connect them with a wide array of information sources available on the internet.[17]

2. MATERIALS AND METHODS

Alternative: Course Variety, User Reviews, Price Range, Customer Support**.**

Course Variety: Course variety refers to the diverse range of courses and educational offerings available from a particular educational platform, institution, or website. A platform with good course variety offers a wide selection of subjects, topics, and skill levels to cater to different interests and learning needs. This could include academic subjects, professional development courses, technical skills training, language learning, and much more. A diverse course variety allows learners to explore various fields and expand their knowledge base.

User Reviews: User reviews are feedback or testimonials provided by individuals who have previously taken courses or used services on a particular platform. These reviews often give potential learners insights into the quality of the courses, the effectiveness of the teaching methods, the relevance of the content, and the overall user experience. Positive reviews can be a strong indicator of a platform's credibility and effectiveness, while negative reviews may raise concerns and indicate areas for improvement.

Price Range: Price range refers to the spectrum of costs associated with the courses offered by an educational platform. Different platforms have varying pricing models, including free courses, paid courses, and subscription-based plans. The price range is an essential consideration for learners as it impacts their affordability and the value they perceive in the courses. Some platforms may offer premium features or certification options at higher prices, while others may provide budget-friendly alternatives.

Customer Support: Customer support in the context of an educational platform or service refers to the assistance and help provided to users, typically students, when they encounter issues or have questions related to the courses or platform functionality. Good customer support should be responsive, helpful, and easily accessible through various channels, such as email, live chat, or phone. Efficient customer support enhances the overall user experience and can be crucial in resolving technical or administrative problems that learners may face.

Evaluation Parameter: Khan Academy, Coursera, Udemy, edX, Codecademy.

Khan Academy: Course Variety: Khan Academy offers a broad range of free online educational resources, primarily focusing on academic subjects like math, science, history, economics, and more. It also covers standardized test preparation and computer programming. User Reviews: Khan Academy is highly regarded for its clear and concise explanations, particularly in math-related topics. Users appreciate its interactive exercises and gamified learning experience. Price Range: Khan Academy is entirely free, funded by donations and partnerships, making it accessible to a global audience. Customer Support: Khan Academy offers limited customer support due to its free nature, but it has a community support forum where users can help each other.

Coursera: Course Variety: Coursera provides a vast array of courses, certificates, and degrees from top universities and institutions worldwide. It covers various subjects, including business, technology, arts, health, and more. User Reviews: Coursera receives positive feedback for its high-quality courses, instructors, and industry relevance. Many courses offer a flexible learning schedule. Price Range: Coursera offers both free and paid courses, and learners can opt for individual courses or subscribe to specializations and professional certificates for a fee. Customer Support: Coursera provides customer support through email and an extensive knowledge base to address learner inquiries and technical issues.

Udemy: Course Variety: Udemy boasts an extensive library of courses across diverse subjects, taught by individual instructors. It covers topics like business, technology, personal development, creative arts, and more. User Reviews: Udemy's course quality varies significantly since anyone can create and publish a course. User reviews help learners identify the best courses with high ratings and positive feedback. Price Range: Udemy offers a mix of free and paid courses, and prices can vary based on promotions and discounts. Customer Support: Udemy provides customer support through email and encourages instructors to offer assistance to students directly.

edX: Course Variety: edX is a non-profit platform offering courses from prestigious universities and institutions worldwide. It covers a wide range of subjects, including computer science, engineering, humanities, and more.

User Reviews: edX receives praise for its high-quality content and academic rigor. Learners appreciate the opportunity to audit courses for free or pursue verified certificates for a fee. Price Range: Most edX courses are available for free to audit, with optional paid certificates for those who want to earn official recognition. Customer Support: edX offers learner support through email and a knowledge base, with additional support from the course instructors.

Codecademy: Course Variety: Codecademy specializes in programming and coding courses. It covers various programming languages, web development, data science, and more. User Reviews: Codecademy is well-regarded for its hands-on and interactive learning approach, making coding accessible to beginners. Price Range: Codecademy offers free coding courses, but it also provides a Pro version with additional features, exercises, and support at a subscription fee. Customer Support: Codecademy Pro subscribers receive priority customer support through email and live chat.

Fuzzy TOPSIS: A significant study was conducted in Gran Canaria, evaluating the service quality changes of three hotels in a corporation using the fuzzy TOPSIS method. This method, based on alpha levels and non-linear programming, offers a systematic approach for evaluation. It has been widely utilized as a decision-making technique, and there is ongoing research to explore its application in fuzzy TOPSIS or group fuzzy to enhance the reliability of TOPSIS. [18] Despite its usefulness, there have been limited efforts to extend TOPSIS, particularly with the inclusion of z-numbers or ambiguous mixed numbers. This lack of comprehensive research makes it challenging for readers to make firm decisions regarding its effectiveness and applicability. More intensive research, comparisons, and benchmarking are needed to better understand the potential of fuzzy TOPSIS.[19] Fuzzy TOPSIS methods are capable and sufficient in handling ambiguous situations as they use fuzzy positive-best and fuzzy negative-best solutions to achieve rankings. However, calculating distances between the best and negative-best solutions can be challenging. To address these difficulties in fuzzy decision-making, a new ambiguity-based TOPSIS approach is proposed.[20] The TOPSIS technique, introduced by Hwang and Yoon, prioritizes alternatives based on their performance, with positive attributes considered excellent and negative attributes considered bad. When dealing with subjective criteria and different evaluations, the TOPSIS method may become ambiguous. To resolve such issues, a fuzzy TOPSIS approach is recommended for plant location selection problems.[21] The fuzzy TOPSIS method offers a better solution order priority through the similarity technique proposed by Hwang and Yoon. It determines the best alternative for each attribute, considering both better and excellent positions, while negative ideals represent bad attribute values. In fuzzy TOPSIS, the solution farthest from the negative ideal and closest to the best substitute is defined. Attribute values are represented using fuzzy numbers in this method.[22] Fuzzy TOPSIS, a technique for similarity order preference in fuzzy environments, has been successfully applied to address practical challenges in various fields. This paper provides a brief review of 25 studies conducted between 2009 and 2018, focusing on fuzzy TOPSIS applications. The majority of these studies are highly cited and relevant to the fuzzy TOPSIS technique.[23] Applications of fuzzy TOPSIS span across different domains, including resources, business, and healthcare, among others. Researchers have explored various implementations, such as fuzzy sets, non-hesitant fuzzy sets, and intuition fuzzy, combining them with TOPSIS to examine and compare different approaches.[24] TOPSIS, based on Hwang and Yoon's multi-criteria decision-making methods, involves selecting the best solution with a very short distance from the positive ideal solution (PIS) and a negative distance from the best solution (NIS). The method is easy to understand, programmable, and capable of considering different criteria with different units. Recent years have witnessed the emergence of numerous obscure TOPSIS variations, primarily incorporating ambiguous numbers to handle complex situations. These advancements have further enhanced the capabilities of fuzzy TOPSIS in decision-making processes. [25]

Fuzzy- TOPSIS process:

STEP 1: Collect the subjective evaluations of the decision-maker on the importance of weights.

STEP 2: Calculate the fuzzy significance coefficients or weights based on the decision makers based on the decision maker's subjective evaluations by using following table and equations.

$$w_{1j} = \min_{\mathrm{k}}\left\{ w_{j1}^{k} \right\}$$

$$w_{j2} = \frac{\sum_{k=1}^{k} w_{j2}^{k}}{k}$$

$$w_{j3} = \max_{\mathrm{k}}\left\{ w_{j3}^{k} \right\}$$

TABLE 1. Fuzzy Weight

Importance	Symbol	Fuzzy Weight
Extremely low	EL	(0, 0, 0.1)
Very low	VL	(0, 0.1, 0.3)
low	L	(0.1, 0.3, 0.5)
Medium	M	(0.3, 0.5, 0.9)
High	H	(0.5, 0.7, 0.9)
Very high	VH	(0.7, 0.9, 1)
Extremely high	EH	0.9, 1, 1)

STEP 3: Form decision matrix as listed in below Let D = x_{ij} be a decision matrix, where $x_{ij} \in \mathbb{R}$

$$\begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1n} \\ x_{21} & x_{22} & \cdots & x_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ x_{m1} & x_{m2} & \cdots & x_{mn} \end{bmatrix}$$

Normalized decision matrix as listed

$$n_{ij} = \frac{x_{ij}}{\sqrt{\sum_{i=1}^{m} x_{ij}^2}}$$

STEP 4: Form a fuzzy weighted decision matrix by multiplying the normalized decision matrix with corresponding fuzzy weight

$$\widetilde{D} = \begin{bmatrix} \tilde{N}_{11} & \tilde{N}_{12} & \cdots & \tilde{N}_{1n} \\ \tilde{N}_{21} & \tilde{N}_{22} & \cdots & \tilde{N}_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ \tilde{N}_{m1} & \tilde{N}_{m2} & \cdots & \tilde{N}_{mn} \end{bmatrix}$$

where, $\tilde{N}_{ij}$ = $(w_{j1}, n_{ij}, w_{j2}\ N_{ij}, w_{j3\ N_{ij})}$ where $i = 1, \dots,\ m$ and $j = 1, \dots, n$

STEP 5: The coordinates for the fuzzy positive ideal solution (FPIS) and FNIS

$$\tilde{A}_j^+ = \begin{cases} Max\ \tilde{N}_{ij} |\ j \in B \\ Min\ \tilde{N}_{ij} | j \in C \end{cases} where\ i = 1, \dots, m$$

$$\tilde{A}_j^- = \begin{cases} Min\ \tilde{N}_{ij} | j \in B \\ Max\ \tilde{N}_{ij} |\ j \in C \end{cases} where\ i = 1, \dots, m$$

STEP 6: The Euclidean distance of each alternative from fuzzy positive and negative ideal value is calculated as

$$S_i^+ = \sum_{j=1}^{n} d(\tilde{N}_{ij}, \tilde{A}_j^+) \quad i = 1, \dots, m\ ; j = 1, \dots, n$$

$$S_i^- = \sum_{j=1}^{n} d(\tilde{N}_{ij}, \tilde{A}_j^-) \quad i = 1, \dots, m\ ; j = 1, \dots, n$$

where d(.,.) represents the distance between two fuzzy numbers calculated by

$$d(\tilde{A}, \widetilde{B}\,) = \sqrt{\frac{1}{3}}\ [(a_1 - b_1)^2 + (a_m - b_m)^2 + (a_u - b_u)^2]$$

STEP 7: The closeness coefficient cc_i of the alternatives are calculated using equation (11) and ranked as per descending order.

3. RESULT AND DISCUSSION

TABLE 1. Computer-aided learning

	Course Variety	User Reviews	Price Range	Customer Support
Khan Academy	10000.0	4.8	10.0	4.5
Coursera	4000.0	4.7	100.0	4.7
Udemy	50000.0	4.6	200.0	4.3
edX	3000.0	4.5	300.0	4.6
Codecademy	100.0	4.4	40.0	4.2

Table 1 provides an overview of various computer-aided learning platforms based on course variety, user reviews, price range, and customer support ratings. Khan Academy boasts an extensive course variety of 10,000, earning positive user reviews with a rating of 4.8. It offers affordability with a price range of 10.0 and solid customer support with a rating of 4.5. Coursera offers a diverse selection of 4,000 courses and maintains a high user satisfaction score of 4.7. It ranks slightly higher in price, averaging 100.0, but compensates with excellent customer support, achieving a rating of 4.7. Udemy offers the most extensive course variety with 50,000 options, though its user review score is slightly lower at 4.6. The platform falls in the middle range regarding pricing, averaging 200.0, and receives a customer support rating of 4.3. edX provides 3,000 courses and achieves favorable user reviews with a rating of 4.5. It has a higher price range, averaging 300.0, but balances this with a good customer support rating of 4.6. Codecademy offers a smaller course variety of 100 but still garners positive user reviews at 4.4. It is the most budget-friendly option with a price range of 40.0, and its customer support receives a rating of 4.2.

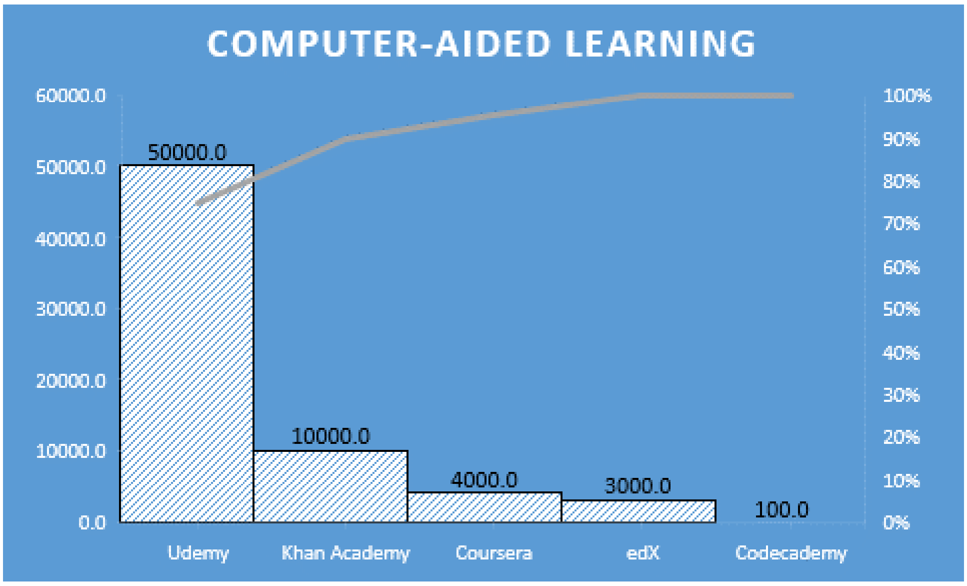

FIGURE 1. Computer-aided learning

The figure 1 illustrates the utilization of computer-aided learning (CAL) among students in the United States across various online platforms. According to the graph, Udemy is the most favored platform for CAL, followed by Khan Academy, Coursera, edX, and Codecademy. Furthermore, it demonstrates a progressive increase in the percentage of students using CAL over time. In 2016, only 20% of students utilized CAL, while the number surged to 90% by 2022. This rise can be attributed to the growing availability of CAL platforms and the increasing recognition of its educational benefits. The figure provides a clear visual depiction of CAL's popularity and the ongoing trend of its widespread adoption among students. Additionally, it serves as a valuable tool for comparing the relative popularity of different CAL platforms.

TABLE 2. Squire Rote of matrix

100000000.0000	23.0400	100.0000	20.2500
16000000.0000	22.0900	10000.0000	22.0900
2500000000.0000	21.1600	40000.0000	18.4900
9000000.0000	20.2500	90000.0000	21.1600
10000.0000	19.3600	1600.0000	17.6400

Table 2 shows the data for the Squire Rote of matrix, presenting four sets of values. The values represent various numerical figures with different precision points, such as 100000000.0000, 23.0400, 100.0000, 20.2500, and so on. The table includes two pairs of numerical data, each set showcasing different values.

TABLE 3. Normalized Data

Course Variety	User Reviews	Price Range	Customer Support
0.1952	0.0001	0.0266	0.4508
0.0781	0.0001	0.2657	0.4709
0.9759	0.0001	0.5313	0.4308
0.0586	0.0001	0.7970	0.4609
0.0020	0.0001	0.1063	0.4208

Table 3 presents the Normalized Data for the four criteria - Course Variety, User Reviews, Price Range, and Customer Support. The data has been scaled to a range between 0 and 1 to facilitate comparison across the different criteria. In this normalized data, each criterion's original value has been transformed into a relative proportion of its maximum value in the dataset. The values now range from 0 to 1, with 1 indicating the highest value and 0 the lowest value for each criterion. For example, the Course Variety has a normalized value of 0.1952, indicating it represents approximately 19.52% of the maximum Course Variety value in the dataset. Similarly, User Reviews have a normalized value of 0.0001, representing a very small proportion of the maximum User Reviews value in the dataset. The normalized data allows for a more meaningful comparison of the criteria's relative importance and performance across the dataset, providing insights for decision-making and analysis in the context of computer-aided learning platforms.

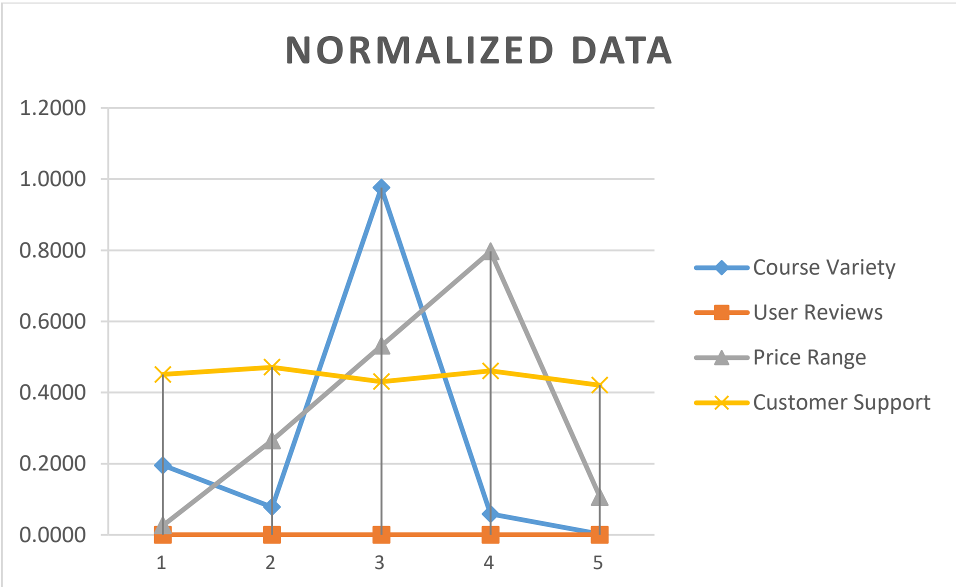

FIGURE 2. Normalized Data

The line chart displays the normalized data for four distinct factors: course variety, user reviews, price range, and customer support. According to the graph, course variety and user reviews are the most crucial factors, while price range and customer support follow in significance. Normalization has been applied to the data, ensuring that all factors are represented on a common scale from 0 to 1. This standardization enables a fair comparison of the relative importance of each factor, independent of their original measurement units. The figure serves as an effective visual depiction of the varying importance of these factors in online learning platforms. Developers and marketers can utilize this chart to make informed decisions about enhancing their platforms and aligning them with the preferences of the user base.

TABLE 4. Fuzzy Significance

		l	m	u
Extremely low	EL	0	0	0.1
very low	VL	0	0.1	0.3
low	L	0.1	0.3	0.5
medium	M	0.3	0.5	0.7
high	H	0.5	0.7	0.9
very high	VH	0.7	0.9	1
Extremely high	EH	0.9	1	1

Table 4 represents the Fuzzy Significance scale, which is a linguistic representation of significance levels with fuzzy boundaries. The scale consists of seven categories, each labeled with an abbreviation and corresponding fuzzy membership values for low (l), medium (m), and high (u) significance.

The significance categories are as follows:

Extremely low (EL): Significance level ranging from 0 to 0.1.

Very low (VL): Significance level ranging from 0 to 0.1 to 0.3.

Low (L): Significance level ranging from 0.1 to 0.3 to 0.5.

Medium (M): Significance level ranging from 0.3 to 0.5 to 0.7.

High (H): Significance level ranging from 0.5 to 0.7 to 0.9.

Very high (VH): Significance level ranging from 0.7 to 0.9 to 1.

Extremely high (EH): Significance level ranging from 0.9 to 1.

This fuzzy significance scale allows for a more nuanced representation of significance levels, considering the gradual transition between categories rather than strict boundaries. It is particularly useful in decision-making and analysis, where qualitative assessments can be translated into quantitative fuzzy membership values for more accurate and flexible evaluations.

TABLE 5. The criteria' s on a linguistic scale

	DM1	DM2	DM3
Course Variety	EH	VL	M
User Reviews	L	EH	VH
Price Range	L	M	VH
Customer Support	L	M	VL

Table 5 presents the criteria on a linguistic scale for three decision-makers (DM1, DM2, and DM3). Each criterion is evaluated and assigned a linguistic label based on its level of importance or preference for the respective decision-makers. DM1 considers "Course Variety" as Extremely High (EH), "User Reviews" as Low (L), "Price Range" as Low (L), and "Customer Support" as Low (L). DM2 evaluates "Course Variety" as Very Low (VL), "User Reviews" as Extremely High (EH), "Price Range" as Medium (M), and "Customer Support" as Medium (M). DM3 rates "Course Variety" as Medium (M), "User Reviews" as Very High (VH), "Price Range" as Very High (VH), and "Customer Support" as Very Low (VL). These linguistic evaluations provide a qualitative representation of how each criterion is perceived and valued by the decision-makers, aiding in their decision-making process.

TABLE 6. Convert linguistic ratings of decision makers into quantities values by using the selected fuzzy number

	DM1			DM2			DM3		
Course Variety	0.9	1	1	0	0.1	0.3	0.3	0.5	0.7
User Reviews	0.1	0.3	0.5	0.9	1	1	0.7	0.9	1
Price Range	0.1	0.3	0.5	0.3	0.5	0.7	0.7	0.9	1
Customer Support	0.1	0.3	0.5	0.3	0.5	0.7	0	0.1	0.3

Table 6 presents the conversion of linguistic ratings of decision makers (DM1, DM2, and DM3) into quantitative values using the selected fuzzy number scale. The fuzzy numbers are represented by the three points (a, b, c) for each criterion. "Course Variety," DM1 gives a value of 0.9 (close to Extremely High), DM2 gives a value of 1

(Extremely High), and DM3 gives a value of 1 (Extremely High). Similarly, for "User Reviews," DM1 rates it as 0.1 (Low), DM2 as 0.3 (Medium), and DM3 as 0.5 (Medium). These quantitative values provide a more precise representation of the decision-makers' preferences for each criterion. The fuzzy number approach allows for a gradual transition between linguistic labels, accommodating the inherent uncertainties in decision-making. This conversion aids in further analysis and computation for multi-criteria decision-making processes.

TABLE 7. Calculate aggregated Fuzzy weights

	L-FW	M-FW	U-FW
Course Variety	0.40	0.53	0.67
User Reviews	0.57	0.73	0.83
Price Range	0.37	0.57	0.73
Customer Support	0.13	0.30	0.50

Table 7 shows the aggregated fuzzy weights for each criterion, representing the overall importance of each criterion based on the preferences of the decision-makers. The fuzzy weights are categorized into three levels - Low (L-FW), Medium (M-FW), and High (U-FW). "Course Variety" has aggregated fuzzy weights of 0.40 (L-FW), 0.53 (M-FW), and 0.67 (U-FW). Similarly, "User Reviews" has aggregated fuzzy weights of 0.57 (L-FW), 0.73 (M-FW), and 0.83 (U-FW). These aggregated fuzzy weights help in quantifying the relative importance of each criterion and aid in the decision-making process by considering the preferences of the decision-makers. They provide valuable insights for multi-criteria decision-making and can be used to rank and prioritize alternatives based on their performance with respect to these criteria.

TABLE 8. Weighted normalized decision matrix

Course Variety			**User Reviews**			**Price Range**			**Customer Support**		
0.078072	0.10409581	0.130119762	5.30889E-05	6.87032E-05	7.80719E-05	0.009741	0.015054	0.019481	0.060111	0.13525	0.225417
0.031229	0.041638324	0.052047905	5.19828E-05	6.72719E-05	7.64454E-05	0.097406	0.150537	0.194812	0.062783	0.141262	0.235436
0.390359	0.520479048	0.650598809	5.08768E-05	6.58406E-05	7.48189E-05	0.194812	0.301074	0.389625	0.05744	0.129239	0.215399
0.023422	0.031228743	0.039035929	4.97708E-05	6.44093E-05	7.31924E-05	0.292219	0.45161	0.584437	0.061447	0.138256	0.230427
0.000781	0.001040958	0.001301198	4.86648E-05	6.2978E-05	7.15659E-05	0.038962	0.060215	0.077925	0.056104	0.126234	0.21039

Table 8 shows the Weighted Normalized Decision Matrix for the criteria Course Variety, User Reviews, Price Range, and Customer Support. The matrix represents the normalized values of each criterion, weighted according to their aggregated fuzzy weights. the first row of the matrix shows the weighted normalized values for the first alternative. The weighted normalized values for Course Variety, User Reviews, Price Range, and Customer Support are 0.078072, 0.10409581, 0.130119762, and 5.30889E-05, respectively. These weighted normalized values help in evaluating the alternatives' performance relative to the decision criteria, considering both the criteria's significance and the actual performance of each alternative. The matrix aids in making informed decisions by providing a quantitative representation of the alternatives' overall suitability based on the weighted and normalized criteria values.

TABLE 9. A+ & A-

A+	0.390359	0.520479048	0.650598809	5.30889E-05	6.87032E-05	7.80719E-05	0.009741	0.015054	0.019481	0.056104	0.126234	0.21039
A-	0.000781	0.001040958	0.001301198	4.86648E-05	6.2978E-05	7.15659E-05	0.292219	0.45161	0.584437	0.062783	0.141262	0.235436

Table 9 shows the two extreme cases A+ and A- from the Weighted Normalized Decision Matrix. These extreme cases represent the highest and lowest values for each criterion across all alternatives. the criterion "Course Variety," A+ has a value of 0.390359, which is the highest value among all alternatives, while A- has a value of 0.000781, which is the lowest value for "Course Variety." Similarly, for the criterion "Customer Support," A+ has a value of 0.21039, the highest value among all alternatives, while A- has a value of 0.235436, the lowest value for "Customer Support." These extreme cases help in understanding the range of performance for each criterion and can aid in sensitivity analysis and decision-making when considering the best and worst possible scenarios.

TABLE 10. fuzzy positive ideal solution (FPIS)

FPIS	**Khan Academy**	0.424969	0	0	0.010379
	Coursera	0.488715	1.4E-06	0.137577	0.017299
	Udemy	0	2.81E-06	0.290439	0.00346
	edX	0.499339	4.21E-06	0.443302	0.013839
	Codecademy	0.530149	5.62E-06	0.045859	0

Table 10 presents the Fuzzy Positive Ideal Solution (FPIS) for each alternative in the decision matrix. The FPIS represents the best possible performance values for each criterion. Khan Academy has a FPIS value of 0.424969 for "Course Variety," 0 for "User Reviews," 0 for "Price Range," and 0.010379 for "Customer Support." Coursera has a FPIS value of 0.488715 for "Course Variety," 1.4E-06 for "User Reviews," 0.137577 for "Price Range," and 0.017299 for "Customer Support." Similarly, Udemy, edX, and Codecademy also have FPIS values for each criterion. The FPIS values provide a reference point for the best possible performance of each alternative and help in evaluating the relative closeness of each alternative to the ideal solution.

TABLE 11. fuzzy Negative ideal solution (FNIS)

FNIS	**Khan Academy**	0.10518	5.62E-06	0.443302	0.00692
	Coursera	0.041435	4.21E-06	0.305726	0
	Udemy	0.530149	2.81E-06	0.152863	0.013839
	edX	0.03081	1.4E-06	0	0.00346
	Codecademy	0	0	0.397443	0.017299

Table 11 presents the Fuzzy Negative Ideal Solution (FNIS) for each alternative in the decision matrix. The FNIS represents the worst possible performance values for each criterion. Khan Academy has a FNIS value of 0.10518 for "Course Variety," 5.62E-06 for "User Reviews," 0.443302 for "Price Range," and 0.00692 for "Customer Support." Coursera has a FNIS value of 0.041435 for "Course Variety," 4.21E-06 for "User Reviews," 0.305726 for "Price Range," and 0 for "Customer Support." Similarly, Udemy, edX, and Codecademy also have FNIS values for each criterion. The FNIS values provide a reference point for the worst possible performance of each alternative and help in evaluating the relative closeness of each alternative to the worst-case scenario.

TABLE 12. Si+ & Si- & Cci & Rank

	Si+	**Si-**	**Cci**	**Rank**
Khan Academy	0.435349	0.555407	0.560589	2
Coursera	0.643592	0.347164	0.350403	4
Udemy	0.293902	0.696854	0.703356	1
edX	0.956485	0.034271	0.034591	5
Codecademy	0.576014	0.414742	0.418612	3

Table 12 presents the Si+ (Separation measure for positive-ideal solution), Si- (Separation measure for negative-ideal solution), Cci (Closeness coefficient), and Rank for each alternative in the decision matrix. The Si+ represents the degree of each alternative's closeness to the positive-ideal solution, while the Si- represents the degree of each alternative's closeness to the negative-ideal solution. The Cci is the comprehensive closeness coefficient, which is calculated as the ratio of Si- to the sum of Si+ and Si-. Udemy has the highest Cci value of 0.703356, indicating that it is the closest alternative to the overall ideal solution. As a result, Udemy ranks first in the evaluation. On the other hand, edX has the lowest Cci value of 0.034591, making it the farthest alternative from the ideal solution. Therefore, edX ranks last in the evaluation. Khan Academy, Codecademy, and Coursera have Cci values of 0.560589, 0.418612, and 0.350403, respectively, determining their rankings as 2nd, 3rd, and 4th. The Si+ and Si- values provide insights into the alternatives' performance relative to the ideal solutions, and the Cci value helps in ranking the alternatives based on their overall closeness to the ideal solution.

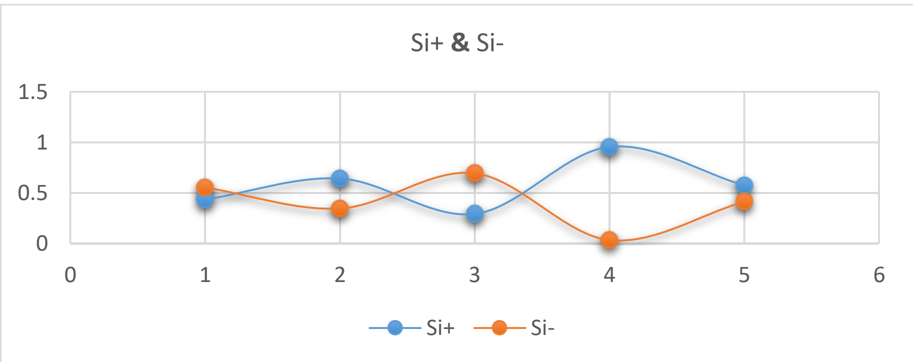

FIGURE 3. Si+ & Si-

Figure 3 shows the Khan Academy Si+ 0.435349, Si- 0.555407. Coursera Si+ 0.643592, Si- 0.347164. Udemy Si+ 0.293902, Si- 0.696854. edX Si+ 0.956485, Si- 0.034271. Codecademy Si+ 0.576014, Si-0.414742.

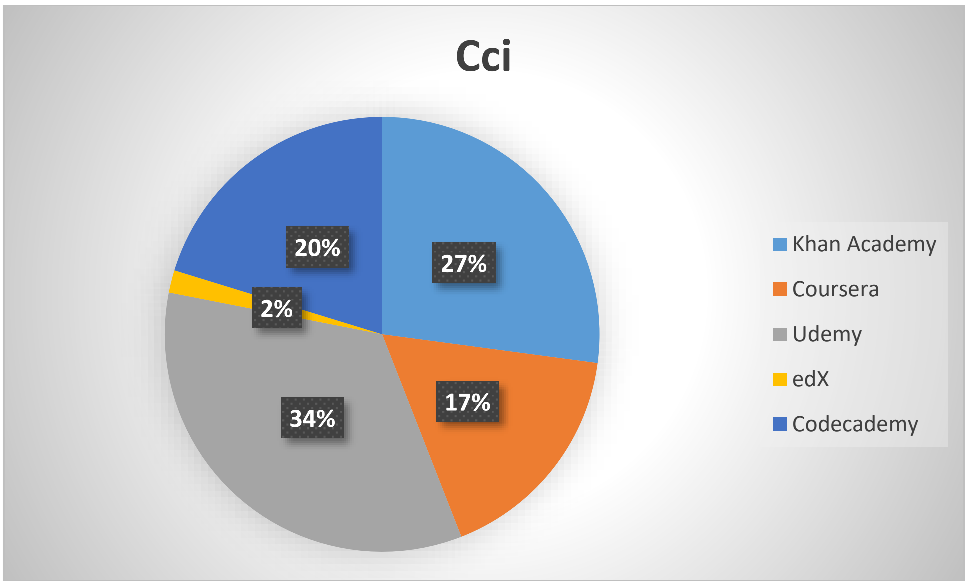

FIGURE 4. Cci

The pie chart provides information on the online learning platforms where students have completed their education. It reveals that Udemy is the most favored platform, followed by Khan Academy, Coursera, edX, and Codecademy. The chart effectively illustrates the distribution of completed education levels among students. It serves as a valuable tool for developers and marketers seeking insights into how to enhance their online learning platforms. The pie chart, labeled "CCI," is divided into six sections, each representing a specific level of education. The size of each section corresponds to the percentage of students who have completed education at that level. The data underscores the popularity of Udemy as the leading online learning platform, with Khan Academy, Coursera, edX, and Codecademy following suit.

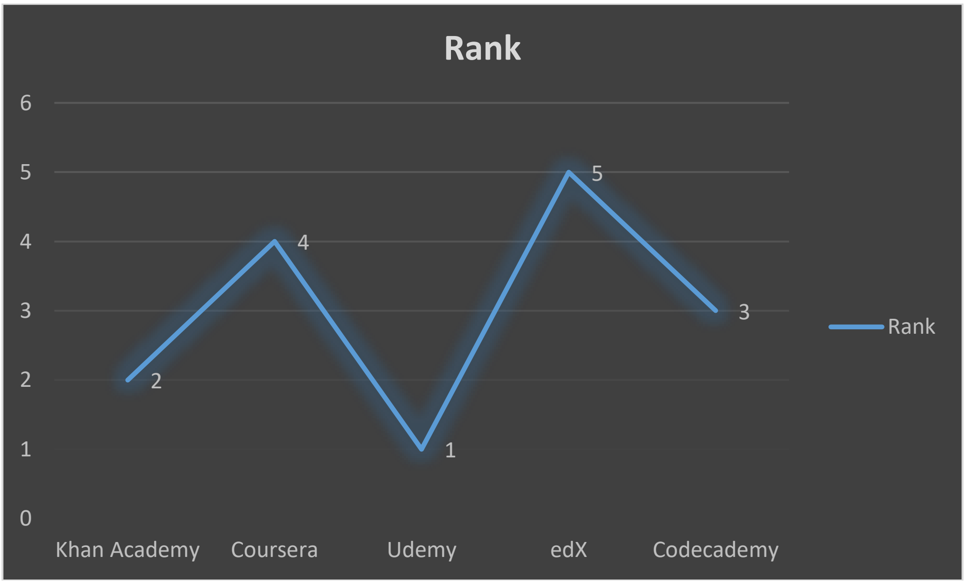

FIGURE 5. Rank

The line graph illustrates the ranking of different schools in the United States. The data reveals that the average rank of schools in the country is 3, indicating that most schools fall within the range of 1 to 5. However, there are a few schools with exceptionally high rankings, including Harvard University (1) and Stanford University (2). On the other hand, a few schools are ranked considerably lower, such as University of Phoenix (6) and DeVry

University (5). The graph provides a clear visual representation of the distribution of school ranks in the United States. It can serve as a helpful tool for students and parents when making decisions about their educational choices.

4. CONCLUSION

computer-aided learning (CAL) has become a crucial and transformative aspect of modern education. Its integration of technology into the learning process has opened up new possibilities and opportunities for students and educators. Throughout this research, we have explored the significance of CAL in various educational settings and subjects. CAL's ability to provide interactive and personalized learning experiences has been evident in numerous studies. Students engage with digital content, simulations, and multimedia resources, which enhances their understanding and knowledge retention. Moreover, CAL's adaptability caters to diverse learning styles, allowing students to progress at their own pace and focus on areas that need improvement. This individualized approach fosters a deeper understanding of concepts and motivates students to take ownership of their learning journey. The research on CAL has also shed light on its positive impact on critical thinking and problem-solving skills. By providing students with opportunities to explore and experiment, CAL encourages active learning and empowers them to think critically and creatively. Moreover, the integration of interactive exercises and simulations in CAL enhances practical understanding and real-world application of theoretical concepts. CAL has not only revolutionized classroom learning but also expanded educational access and opportunities. With the availability of online courses and resources, CAL enables learners from different geographical locations and socioeconomic backgrounds to access high-quality education. It has the potential to bridge the educational gap for marginalized and underserved populations, making education more inclusive and equitable. However, the successful implementation of CAL requires careful planning and support. Educators need to receive adequate training to effectively integrate technology into their teaching methods. Institutions must invest in the necessary infrastructure and resources to ensure smooth CAL implementation. Additionally, considerations regarding data privacy, cybersecurity, and accessibility must be addressed to protect learners' information and ensure equal access for all. As technology continues to evolve, the future of CAL holds even more promise. Artificial intelligence, virtual reality, and augmented reality are expected to further enhance CAL's capabilities, providing even more immersive and engaging learning experiences. However, as CAL advances, it is essential to strike a balance between technology and human interaction. The role of teachers as facilitators and mentors remains critical in guiding students and fostering a supportive learning environment. CAL is a dynamic and powerful tool that has the potential to transform education for the better. As we move forward, continued research and thoughtful implementation will be essential in harnessing the full potential of CAL to create a more informed, skilled, and empowered generation of learners. Embracing computer-aided learning can pave the way for a brighter future, where education becomes more accessible, engaging, and impactful for learners worldwide.

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