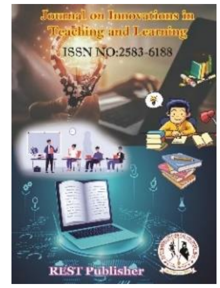
Journal on Innovations in Teaching and Learning

Vol: 4(2), June 2025

REST Publisher; ISSN: 2583 6188

Website: http://restpublisher.com/journals/jilt/

DOI: https://doi.org/10.46632/jitl/4/2/1



The Evolution of E-Learning and Teaching Using Artificial Intelligence

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Abstract: *E-learning has transformed the landscape of education and professional training by providing accessible and flexible learning solutions. The integration of artificial intelligence (AI) into e-learning platforms has further revolutionized the learning experience by enabling personalized content delivery, intelligent tutoring systems, adaptive assessments, and real-time feedback. This study employs the TOPSIS method to evaluate and rank popular e-learning platforms, identifying Thinkific as the best-performing platform, followed by Codecademy, Learning, Pluralsight, and Skillshare in descending order. The results indicate that platforms emphasizing structured content, interactivity, specialized courses, and AI-driven features perform better in terms of user satisfaction and learning outcomes.*

The findings highlight the importance of selecting the right e-learning platform based on the learner's objectives and the platform's technological capabilities. AI enhances this process by offering data-driven insights and tailored learning paths, which significantly improve engagement and knowledge retention. Moreover, continuous improvements in course design, AI integration, and learner support systems are essential to maximize the effectiveness of online education. Future research could explore additional evaluation parameters, including AI-driven analytics and user feedback mechanisms, for a more comprehensive assessment of e-learning platforms.

The significance of this research lies in evaluating and selecting effective e-learning platforms using the TOPSIS method, underlining the growing importance of AI in shaping modern digital education. As online education expands, understanding which platforms leverage AI to provide the best learning experiences is crucial for educators, students, and organizations. This study offers valuable insights into platform performance across multiple criteria, aiding in strategic decision-making, optimizing resource allocation, and enhancing overall educational quality. Additionally, it encourages continued innovation by identifying key factors—including AI functionalities—that influence learning success. Structured decision-making approaches like TOPSIS, when combined with emerging AI capabilities, provide a powerful framework for evaluating and improving digital learning strategies.

Key words: *E-learning, teaching method, Multi-criteria decision-making method (MCDM), TOPSIS method, Online learning platforms, Educational technology, Learning management systems (LMSDistance learning Digital educationStudent engagement*

1. INTRODUCTION

Higher education has undergone a substantial transformation, shifting from conventional teaching methods to modern strategies that incorporate computer technology. These innovations have significantly enhanced both the delivery and acquisition of knowledge. Technological progress, particularly the rise of artificial intelligence (AI), has provided new avenues for refining instructional techniques and improving students' learning capabilities. A study examining the impact and effectiveness of e-learning at OTC revealed that both students and instructors shared positive views, rating e-learning highly across five performance indicators. Participants acknowledged e-learning as a powerful tool for enhancing instructional delivery and facilitating deeper knowledge acquisition through improved learning transfer.

AI plays a critical role in this evolution by enabling adaptive learning systems that respond to individual student needs. These intelligent systems can assess learner performance in real time, delivering personalized content and adjusting learning paths accordingly. For instance, AI algorithms can recommend study materials based on students' progress and preferences, increasing engagement and motivation—especially when learners are given autonomy in material selection, a concept known as "direct interest." Research shows that such self-directed choices lead to more effective learning outcomes.

In middle school settings (grades 6–9), teachers provide initial scaffolding to help students select challenging yet stimulating materials. AI tools can further support this by analyzing learners' profiles and suggesting resources aligned with their interests and cognitive levels. This shift toward more customized learning is changing traditional teaching strategies, making instruction more efficient and outcomes more meaningful. While a grammar- and vocabulary-centric approach may help students pass exams, AI-driven e-learning supports more holistic language acquisition and real-world application. E-learning, defined as a process supported by digital content delivery, networked services, and instructor guidance, reflects a departure from traditional models. It embraces a learner-centered paradigm characterized by personalization, flexibility, and autonomy. AI enhances these qualities by dynamically adapting content, pace, and assessment methods based on user behavior and performance. The use of AI in e-learning allows learners to control their educational journeys, setting goals and navigating materials in ways that align with their needs. Decision-makers often view e-learning as an innovative, cost-effective alternative to conventional methods. AI strengthens this perspective by helping teachers optimize instructional strategies and providing valuable insights into learner progress and behavior. This transformation has altered how educational systems manage, deliver, and evaluate information. Numerous initiatives have been developed to integrate AI-powered digital resources and platforms within educational institutions to support learning and development. Though the definition of e-learning varies by context, it is often understood as the integration of information and communication technologies (ICT) to promote independent, technology-assisted learning. AI plays a central role in this integration, offering tools that evaluate the effectiveness of teaching methods and support continuous improvement. Effective e-teaching, facilitated by AI, is not universally defined, as it depends on perspectives regarding quality instruction and learning outcomes. However, consensus is growing around the importance of personalized, data-informed teaching strategies. Research has identified key factors influencing e-learning satisfaction: user characteristics, organizational dynamics, and e-learning-specific features. AI systems mediate these factors by enhancing usability and providing tailored feedback. Despite increased interest in e-learning evaluation, research remains limited. As the cost of implementing AI-based e-learning solutions is considerable, rigorous evaluation is essential. Emerging evaluation models emphasize management-oriented approaches, incorporating AI tools to measure and optimize implementation. AI-driven e-learning significantly contributes to the economic growth of individuals and society. In a rapidly evolving global economy, workers must continuously acquire new skills. AI facilitates this lifelong learning by offering rapid, accessible, and personalized educational experiences. It supports formal and informal learning alike, addressing the growing demand for a highly skilled, tech-savvy workforce.

Historically, e-learning evolved from correspondence courses to today's AI-enhanced virtual classrooms. Technologies such as chat platforms, discussion forums, video conferencing, and collaborative tools enable rich, interactive learning environments. AI enhances these platforms by analyzing communication patterns, moderating discussions, and supporting learners through intelligent tutoring systems.

ICT, encompassing information technology, telecommunications, and audiovisual tools, has transformed global communication and education. The Internet has made real-time learning possible, but it also introduces challenges such as digital equity and content overload. AI helps navigate these challenges by curating high-quality, relevant content and supporting educators with data-informed decisions. Modern e-learning platforms integrate AI to deliver remote instruction, personalize learning, and monitor progress. While creating customized e-learning programs demands expertise, learning management systems powered by AI simplify the process by automating course delivery and feedback. Many of these systems follow a constructivist approach, encouraging students to take ownership of their learning. Self-regulated learners benefit from AI tools that foster motivation, independence, and metacognitive strategies. artificial intelligence is a driving force behind the evolution of e-learning. By enabling personalization, automation, and continuous improvement, AI not only enhances the quality and efficiency of education but also helps bridge the gap between traditional instruction and the demands of modern learners.

Adaptive learning is a technology-driven educational method that delivers customized learning experiences based on each learner's unique needs, preferences, and progress. By using artificial intelligence and data analytics, it continuously adjusts instructional content, format, and pace according to the learner's performance and level of engagement. This personalized approach enhances learning efficiency, boosts student involvement, and leads to improved educational outcomes. This discussion emphasizes the value of adaptive learning in e-learning environments, showcasing its key advantages. Adaptive learning systems utilize machine learning algorithms to collect, process, and interpret extensive learner data. This data-centric approach allows for real-time customization of the learning experience by delivering personalized content, resources, and activities aligned with each learner's abilities and objectives. By tailoring individual learning pathways, these systems support self-paced progression, deliver targeted assistance, and create a more engaging and effective educational experience. The integration of artificial intelligence further enhances these systems by enabling continuous improvement through pattern recognition, performance analysis, and the generation of tailored recommendations and interventions. Additionally, adaptive learning systems provide valuable insights into the effectiveness of instructional strategies and materials, allowing educators and instructional designers to refine and enhance the e-learning environment for better outcomes.

2. MATERALS AND METHODS

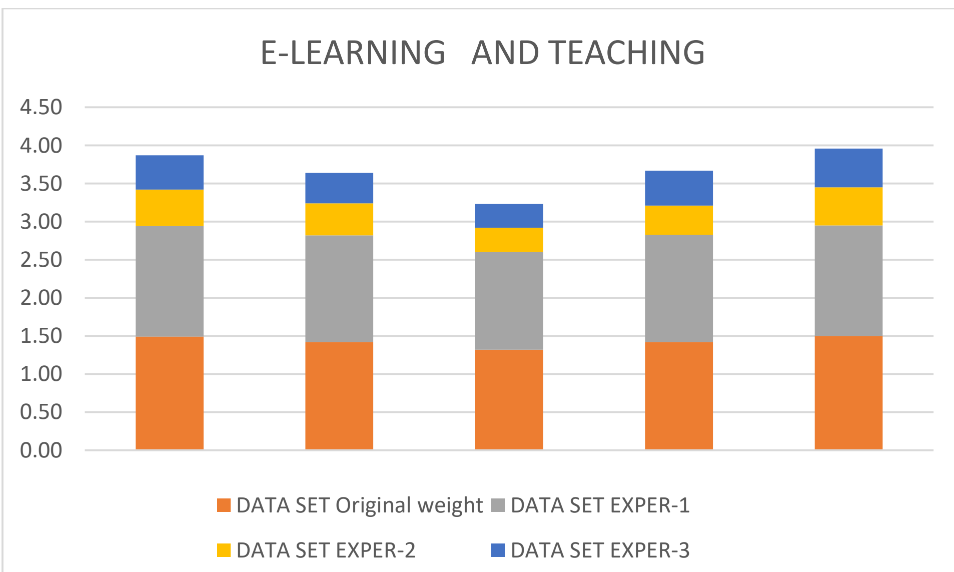
MCDM models play a crucial role in evaluating alternatives and selecting the most suitable criteria for decision-making. These models combine computational and mathematical approaches to enable decision-makers to subjectively assess performance criteria.. For TEL to be effective, enhancements should be considered during the technology design phase to improve assessment methods. However, a notable drawback of enhancement is its potential impact on interrelated cognitive skills, as the development of one skill may inadvertently hinder the progress of others over time. Another notable feature of this study is that the proposed algorithms can be applied not only to e-learning systems, but also to other systems that involve subjective judgments. These components can be adjusted – expanded or improved – based on the specific needs of institutions and students. In addition, the findings of this study can be directly applied to the evaluation of e-learning providers. This research followed three main steps: conducting a literature search, selecting relevant studies, and extracting and summarizing the data. Furthermore, the criteria that contribute to the success of e-learning systems are identified by using the gap-valued type-2 fuzzy AHP technique. This study introduces two systems: one that combines the TOPSIS method with information gain and the other that combines the AHP method with information gain. Both systems share the same architectural framework. The primary goal is to establish a comprehensive and refined approach to selecting AR providers using these methods. The selection of the Delphi method, TOPSIS, and SFSs is driven by their alignment with the objectives of the study, and their ability to effectively navigate the issues of educational AR provider selection, ensuring well-informed decision-making. Despite the focus on educational research, innovation in higher education is influenced by many factors. To address various criteria relevant to assessing innovation performance in higher education institutions, we have integrated DEMATEL, fuzzy ANP, and TOPSIS methods to create an innovation support system. E-learning and teaching have evolved significantly with the integration of multi-criteria decision-making (MCDM) methods, such as the Top-Priority Sorting Technique by Similarity (TOPSIS). This approach improves decision-making by systematically evaluating various alternatives based on predefined criteria. In the context of e-learning, TOPSIS helps educators and learners evaluate and rank various online learning platforms, instructional methods, and technology tools to determine the most effective solutions for educators and learners. By using the TOPSIS method, organizations can evaluate e-learning platforms based on factors such as usability, accessibility, engagement, cost-effectiveness, and overall learning outcomes. This ensures that the selected platform is aligned with educational goals and increases student satisfaction. Furthermore, TOPSIS facilitates data-driven decisions by measuring subjective evaluations, allowing for a more objective comparison of different e-learning solutions. In addition, this method plays a key role in selecting digital teaching tools that enhance the virtual learning experience. By prioritizing factors such as interactivity, adaptability, and efficiency, educators can implement technologies that best support student engagement and knowledge retention. As e-learning continues to evolve, the use of MCDM methods such as TOPSIS provides a structured and reliable approach to improving online education, making learning accessible, efficient, and effective for diverse learners. **Alternative:** E-learning has revolutionized modern education by providing flexible, accessible, and interactive learning experiences. With the advancements in technology, digital learning platforms offer a wide range of courses to suit a variety of learners. These platforms incorporate a variety of teaching methods, including video lectures, interactive exercises, and project-based learning, making education more engaging and effective. E-learning supports independent and structured learning, allowing students and professionals to improve skills at their own pace. Alternative platforms for e-learning **Plural Vision** - A comprehensive platform focused on technology and creative skills, offering in-depth courses on programming, cyber security, and software development. **Code Academy** - Perfect for learners interested in coding, offering interactive lessons in programming languages such as Python, Java, and JavaScript. **Thinkific -** Perfect for educators and entrepreneurs who want to create and sell their own online courses with customizable content and student engagement tools. **LinkedIn Learning** - A professional development platform that offers business, technology, and creative courses to help users advance in their careers**. Skill share** - A creative learning platform that offers courses in design, photography, writing, and entrepreneurship, fostering a community-based learning approach. **Evaluation Parameter: Content Quality** - Assesses how accurate, comprehensive, and relevant the course materials are. Engagement Level - Measures how interactive and immersive the learning experience is. Accessibility - Examines ease of use across devices and operating systems. Learning Outcomes - Assesses student knowledge retention and skill application. **Instructor Support** - Analyzes the availability of instructor guidance and responsiveness to student inquiries. **Technical Performance** - Reviews site reliability, speed, and overall performance. Evaluation Methods - Considers the effectiveness of quizzes, tests, and feedback systems**.** Cost-Effectiveness - Determines whether the site provides good value for money.

3. ANALIYSIS AND DISCUSION

TABLE 1. Data Set

Alternatives	Original weight	EXPER-1	EXPER-2	EXPER-3
plural sight	1.49	1.45	0.48	0.45
codecademy	1.42	1.40	0.42	0.40
Thinkific	1.32	1.28	0.32	0.31
Learning	1.42	1.41	0.38	0.46
Skill share	1.50	1.45	0.50	0.51

E-learning has transformed the educational landscape, providing learners with a variety of options for acquiring knowledge and skills through digital platforms. Different online learning providers offer different features, teaching methods, and user experiences, making it necessary to evaluate them based on performance metrics. In this study, five popular e-learning platforms – Plural Sight, Codecademy, and Thinkific, Learning, and Skill share – are analyzed based on their performance in delivering online education. The dataset considers four evaluation tests (Original weight, EXPER-1, EXPER-2, and EXPER-3) to assess how each platform performs under different conditions. Plural Sight has a higher original weight (1.49) but shows a decline in the later tests (0.45 in EXPER-3), indicating variations in performance. Codecademy and Thinkific also show similar trends, with their scores decreasing slightly across the tests. Learning remains stable, showing a slight improvement in EXPER-3 (0.46), while Skill share continues to maintain its performance with a high score in EXPER-3 (0.51) .This comparative analysis highlights the dynamic nature of e-learning platforms and their varying levels of performance. The results suggest that platforms such as Skill share and Learning continue to perform well, making them strong contenders for effective digital education. Continuous evaluation ensures that platforms are selected that meet the needs of learners.



FIGIUR 1. E-Learning and Teaching

The bar chart illustrates the performance evaluation of e-learning platforms based on four different datasets: original weight, EXPER-1, EXPER-2, and EXPER-3. The evaluation provides insights into how each dataset contributes to the overall evaluation of online learning platforms. From the graph, the original weight (orange section) represents the baseline performance of the platforms before experimental adjustments. The EXPER-1 dataset (gray section) appears to be the most significant contributing factor in each instance, indicating its strong influence in the evaluation process. The EXPER-2 dataset (yellow section) has a small proportion, indicating that it may have a limited impact on the final evaluation. Finally, the EXPER-3 dataset (blue section), although small in contribution, plays a role in refining the overall evaluation. The variation in bar heights suggests that while some sites maintain consistent performance across trials, others exhibit fluctuations, reflecting potential differences in instructional quality, learner engagement, and site adaptability. The findings emphasize the importance of continuous evaluation in selecting the most effective e-learning site. The dataset highlights the dynamic nature of online learning sites, where multiple evaluation parameters influence their performance. A thorough analysis of these datasets will help educators and learners make informed decisions about the most appropriate e-learning sites.

TABLE. 2 Normalized Data

plural sight	0.4655	0.4634	0.5050	0.4666
codecademy	0.4436	0.4474	0.4418	0.4147
Thinkific	0.4124	0.4091	0.3366	0.3214
Learning	0.4436	0.4506	0.3998	0.4769
Skill share	0.4686	0.4634	0.5260	0.5288

Normalized data provides a clear comparison of different e-learning platforms by adjusting the values to a common scale. This process ensures that the variations in the dataset reflect the true differences in performance, without being affected by different units of measurement. From the given table, Skill Sharing (0.4686, 0.4634, 0.5260, and 0.5288) shows the highest normalized values in most of the tests, indicating its strong performance across various metrics. Plural View (0.4655, 0.4634, 0.5050, and 0.4666) follows closely, showing consistent and competitive performance. Codecademy (0.4436, 0.4474, 0.4418, 0.4147) and Learn (0.4436, 0.4506, 0.3998, 0.4769) show moderate variations, indicating some fluctuations in their performance. Thinkific (0.4124, 0.4091, 0.3366, and 0.3214) has the lowest normalized values, which may indicate areas for improvement compared to other platforms.

TABLE 3. Weight

plural sight	0.25	0.25	0.25	0.25
codecademy	0.25	0.25	0.25	0.25
Thinkific	0.25	0.25	0.25	0.25
Learning	0.25	0.25	0.25	0.25
Skill share	0.25	0.25	0.25	0.25

The weight distribution for e-learning platforms – Plural View, Code Academy, Thinking, Learning and Skill Sharing – is assigned equally across all tests, with a fixed value of 0.25 for each platform in each category. This uniform weighting implies that all platforms are evaluated on an equal basis, with no bias towards a particular platform. In a typical multi-criteria decision-making (MCDM) analysis, the weights represent the importance assigned to each alternative. Here, since all platforms have equal weights, it implies that no single platform is given priority over another, ensuring a fair comparison. However, in practical applications, assigning different weights based on factors such as course quality, learner engagement and accessibility may provide a more insightful assessment. Equal weight distribution facilitates the comparison process by ensuring neutrality in the assessment. However, for a more refined analysis, adjusting the weights based on actual user preferences, industry trends, and learning outcomes can provide a more accurate reflection of site performance. This balanced approach ensures that the evaluation remains unbiased while allowing for a comprehensive evaluation of e-learning solutions.

TABLE. 4 Weighted normalized decision matrix

plural sight	0.1164	0.1158	0.1262	0.1166
codecademy	0.1109	0.1119	0.1105	0.1037
Thinkific	0.1031	0.1023	0.0842	0.0804
Learning	0.1109	0.1127	0.0999	0.1192
Skill share	0.1172	0.1158	0.1315	0.1322

Combining the two provides a refined assessment of e-learning platforms Plural View, Codecademy, Thinkific, Learn, and Skill share. The values in this matrix reflect the relative performance of each platform after incorporating weight adjustments. Across platforms, Skill share shows higher weighted normalized values across multiple categories, especially in the last two tests (0.1315 and 0.1322). This indicates that Skill share performs better when evaluated with weighted criteria. Plural View also maintains strong values, indicating consistent performance across all categories. In contrast, Thinkific has the lowest weighted normalized values (0.0842 and 0.0804), indicating relatively weak performance compared to other platforms. The weighted normalized decision matrix provides a structured and fair approach to comparing e-learning platforms based on multiple criteria. These results highlight performance variations between platforms, emphasizing the need for further analysis based on specific user needs, such as course diversity, interactivity, and industry relevance. While some platforms, such as Skill Sharing and Multifaceted Viewpoint, appear to be strong contenders, others may need improvements in specific areas to improve their competitiveness in the e-learning arena.

TABLE. 5 Positive Matrix

plural sight	0.1172	0.1158	0.0842	0.0804
codecademy	0.1172	0.1158	0.0842	0.0804
Thinkific	0.1172	0.1158	0.0842	0.0804
Learning	0.1172	0.1158	0.0842	0.0804
Skill share	0.1172	0.1158	0.0842	0.0804

The positive matrix represents the best possible values in the estimated criteria for e-learning platforms, ensuring a uniform quality for comparison. In this matrix, all platforms – Plural View, Codecademy, Thinking, Learning, and Skill Sharing – share similar values (0.1172, 0.1158, 0.0842, and 0.0804), indicating that each platform has similar potential in terms of their highest performance on the weighted decision criteria. This uniformity, viewed from an idealistic standpoint, implies that no single platform has a distinct advantage over the others based on the criteria used. Instead, the variations observed in the previous matrices (such as the weighted normalized decision matrix) are likely due to differences in individual performance rather than a fundamental difference in their potential capabilities. The positive matrix serves as a benchmark for assessing how well each platform performs relative to a best-case scenario. Since all platforms show similar positive values, the difference between them must come from other aspects such as real-world implementation, user experience, or additional qualitative factors. Future evaluations should include qualitative insights to complement the numerical analysis and ensure a comprehensive evaluation of e-learning platforms.

TABLE 6. Negative matrix

plural sight	0.1031	0.1023	0.1315	0.1322
codecademy	0.1031	0.1023	0.1315	0.1322
Thinkific	0.1031	0.1023	0.1315	0.1322
Learning	0.1031	0.1023	0.1315	0.1322
Skill share	0.1031	0.1023	0.1315	0.1322

The negative matrix represents the worst possible values in the evaluated criteria for e-learning sites. In this case, the values for Plural View, Codecademy, Thinkific, Learning, and Skill Sharing are similar (0.1031, 0.1023, 0.1315, and 0.1322), indicating that each site has the same minimum performance when evaluated against the given evaluation parameters. This uniformity indicates that, at least in the way the evaluation is structured, all sites face similar limitations or weaknesses. Since negative values in the dataset indicate the least favorable performance, they highlight areas where each site may need improvement. These include aspects such as user engagement, content accessibility, or technical adaptability. The negative matrix provides a basis for understanding the weak points of performance of each e-learning site. Since all sites share the same values, their shortcomings are evenly distributed, meaning that external factors such as usability, instructor quality, or additional features may be the real differentiating factors. Future evaluations should include qualitative assessments to better understand how each platform mitigates these weaknesses in practice

TABLE 7. SI Plus

	SI Plus
plural sight	0.0556
codecademy	0.0359
Thinkific	0.0195
Learning	0.0425
Skill share	0.0702

He SI Plus (Similarity to Ideal Positive Solution) values indicate how close each e-learning platform is to the ideal performance. A higher SI Plus value indicates a better alignment with the ideal learning environment. Skill Share has the highest SI Plus value (0.0702), indicating that it is the best performing platform of the five. This indicates a strong fit in terms of content delivery, accessibility, and overall user experience. Plural View follows with a value of 0.0556, which performs better, but slightly lower than Skill Share. Learn and Codecademy have intermediate values (0.0425 and 0.0359, respectively), indicating moderate performance. Thinkific has lowest SI Plus score (0.0195), meaning that it is the least aligned with the ideal learning conditions based on this assessment. The SI Plus scores provide an objective ranking of e-learning platforms, with Skill share emerging as the best performer and Thinkific ranking the lowest. These results suggest that platforms with higher scores are better suited for teaching and learning, while platforms with lower scores may need improvements in content quality, usability, or learner engagement.

TABLE .8 Si Negative

	Si Negative
plural sight	0.0251
codecademy	0.0375
Thinkific	0.0702
Learning	0.0365
Skill share	0.0195

The SI Negative (equivalent to Ideal Negative Solution) values indicate how far each e-learning platform is from poor performance. A lower SI negative value indicates better performance, meaning the platform is less similar to an ineffective learning system. Skill share has the lowest SI negative value (0.0195), indicating the lowest similarity to an ineffective system and, therefore, one of the best choices for e-learning. Plural View follows with 0.0251, showing that it maintains strong performance with minimal negative impact. Learn and Codecademy have moderate SI negative values (0.0365 and 0.0375, respectively), suggesting room for improvement in certain areas. Thinkific has the highest SI negative score (0.0702), meaning it is very similar to an ineffective e-learning system that may need to improve content delivery, engagement, or usability. The negative SI values confirm that skill sharing and plural vision are the most useful platforms, as they are very rarely associated with poor performance indicators. On the other hand, Thinkific needs improvements to compete effectively with other e-learning options.

TABLE 9. Ci values

	Ci
plural sight	0.3112
codecademy	0.5109
Thinkific	0.7822
Learning	0.4618
Skill share	0.2178

The Ci (Coefficient of Closeness) indicates how close each e-learning platform is to the best solution. A low Ci value indicates better performance, while a high Ci indicates that the platform is further away from the best learning environment. Skill share has the lowest Ci value (0.2178), making it the closest to the best e-learning solution and the best performing platform. Plural View follows with a Ci value of 0.3112, showing that it is more effective but slightly less optimal than Skill share. Learning has a moderate score (0.4618), indicating good performance but with room for improvement. Codecademy has a high Ci value (0.5109), indicating that improvements may be needed in its learning methods or engagement strategies. Thinkific has the highest Ci value (0.7822), which is far from the best learning experience. This indicates that significant improvements are needed in areas such as user experience, content delivery, and overall performance. Based on Ci values, Skill share and Plural view are the most efficient e-learning platforms. Meanwhile, Thinkific is the least efficient, requiring major improvements to align with best practices in online education.

TABLE 10. Rank

	Rank
plural sight	4
codecademy	2
Thinkific	1
Learning	3
Skill share	5

The ranking of e-learning platforms is based on their Ci (Closeness Coefficient) values, which determine their effectiveness in providing an optimal learning experience. A lower Ci value indicates a better platform, leading to a higher ranking. Thinkific ranks 1st, meaning it has the best overall performance among the platforms evaluated. This indicates that it excels in key areas such as content delivery, accessibility, and user experience. Codecademy ranks 2nd, indicating strong performance but has small areas for improvement. Learn is ranked 3rd, reflecting its moderate performance in online education. Plural View ranks 4th, indicating that while it is a good platform, there are better alternatives in terms of overall e-learning performance. Skill share ranks 5th, indicating that it is the least effective of the platforms evaluated. This indicates that it may need significant improvements in factors such as content quality, teaching methods, or user engagement. Thinkific and Code Academy stand out as the most useful e-learning platforms in the rankings. Meanwhile, Skill Share ranks very low, highlighting the need for improvements to compete with the top-ranked platforms.

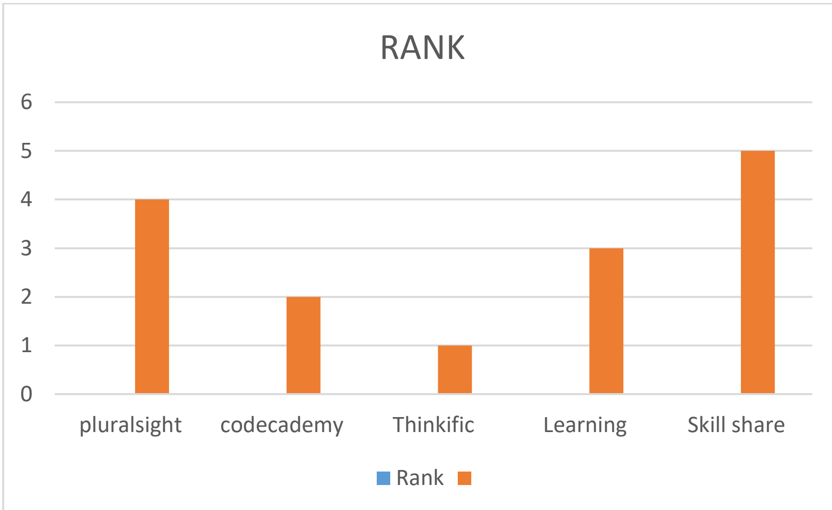


FIGURE 2. Rank

The bar chart illustrates the rankings of various e-learning platforms based on the Multi-Criteria Decision Making (MCDM) methodology. The rankings are determined by evaluating factors such as accessibility, course quality, user engagement, and overall performance .From the chart, Thinkific ranks 1st, making it the most effective platform among those evaluated. This indicates that Thinkific offers an optimal learning experience, excelling in aspects such as structured courses, interactive content, and usability. Code Academy follows closely at 2nd, showing a strong position in providing high-quality coding and programming courses. It is a preferred choice for learners interested in technical skills. Learn is ranked 3rd, indicating a moderate level of performance, meaning it meets some learning expectations but may have areas that need improvement. Plural View is ranked 4th, indicating that it is a useful platform, but lags behind top competitors in some areas, such as user interaction or course diversity. Skill share, ranked 5th, is the least performing of the platforms evaluated. This indicates that improvements may be needed in content depth, user engagement, or course structure. Based on this analysis, Thinkific and Code Academy emerge as the leading platforms, while Skill share needs improvement to compete with higher-ranked e-learning service.

4. CONCLUSION

The integration of multi-criteria decision-making (MCDM) methods, especially the technique for prioritizing similarity (TOPSIS), has significantly improved decision-making in e-learning and teaching. In the digital education landscape, selecting the most effective platforms, teaching strategies, and technology tools is crucial to ensuring high-quality learning experiences. TOPSIS helps organizations and educators systematically evaluate various e-learning alternatives based on multiple criteria, such as accessibility, engagement, cost, and overall effectiveness. By using the TOPSIS method, decision-makers can analyze and rank e-learning tools, ensuring that the most appropriate options are selected to improve teaching efficiency and student learning outcomes. This method allows for structured evaluation by measuring subjective factors, making comparisons more objective and data-driven. In addition, it assists in selecting appropriate digital tools that promote interactivity, adaptability, and user satisfaction. The use of TOPSIS in e-learning and teaching ensures a structured, objective, and efficient approach to decision-making. By prioritizing critical success factors, educational institutions can improve their digital learning environments, ultimately improving student engagement and knowledge retention. As e-learning continues to evolve, MCDM methods such as TOPSIS will play a key role in improving the quality and accessibility of education worldwide.

REFERENCES

[1]. Encarnacion, Riah F. Elcullada, Annjeannette Alain D. Galang, and Byron Joseph A. Hallar. "The impact and effectiveness of e-learning on teaching and learning." *Online Submission* 5, no. 1 (2021): 383-397

[2]. Cai, Huiwei. "E-learning and English Teaching." *Ieri Procedia* 2 (2012): 841-846.

[3]. Alenezi, Abdullah. "The role of e-learning materials in enhancing teaching and learning behaviors." *International Journal of Information and Education Technology* 10, no. 1 (2020): 48-56.

[4]. Mohammad, Mohammad. "The impact of e-learning and e-teaching." *World Academy of Science, Engineering and Technology* 62 (2012): 408-413.

[5]. Cheok, Mei Lick, and Su Luan Wong. "Predictors of e-learning satisfaction in teaching and learning for school teachers: A literature review." *International Journal of Instruction* 8, no. 1 (2015): 75-90.

[6]. Anderson, Jonathan. "IT, e-learning and teacher development." *International Education Journal* 5, no. 5 (2005): 1-14.

[7]. Attwell, Graham. "Evaluating E-learning: A Guide to the Evaluation of E-learning." *Evaluate Europe Handbook Series* 2, no. 2 (2006): 1610-0875.

[8]. Hamad, Asma Lutfi, Hayah Mohamed Abouelnaga, Ahmed Baz Mohamed Metwally, Hany ShoShan, and Nisren Farouk Moawad. "The Importance of E-Learning to the Students and Teachers." *Journal of Language and Linguistic Studies* 18, no. 2 (2022): 952-968.

[9]. Kotzer, Shulamit, and Yossi Elran. "Learning and teaching with Moodle-based E-learning environments, combining learning skills and content in the fields of Math and Science & Technology." (2012): 122-131.

[10]. Oliver, Ron, and Jan Herrington. "Teaching and learning online: A beginner's guide to e-learning and e-teaching in higher education." (2001).

[11]. Ouadoud, Mohammed, Nouha Rida, and Tarik Chafiq. "Overview of E-learning Platforms for Teaching and Learning." *Int. J. Recent Contributions Eng. Sci. IT* 9, no. 1 (2021): 50-70.

[12]. Bezhovski, Zlatko, and Subitcha Poorani. "The evolution of e-learning and new trends." In *Information and Knowledge Management*, vol. 6, no. 3. 2016.

[13]. Cazan, Ana-Maria, and Catalin-Ioan Maican. "Factors Determining the Use of e-Learning and Teaching Satisfaction." *Comunicar: Media Education Research Journal* 31, no. 74 (2023): 83-93.

[14]. Simpong, Derweanna Bah, Roslizawati Che Aziz, Nik Alif Amri Nik Hashim, Raja Norliana Raja Omar, Abdullah Muhamed Yusoff, Nur Hafizah Muhammad, Tahirah Abdullah, Siti Afiqah Zainuddin, and Fauzan Hafiz Muhammad Safri. "Teaching and learning in higher education: E-learning as a tool." *International Journal of Innovative Technology and Exploring Engineering (IJITEE)* (2020).

[15]. Uden, Lorna, Ince Trisnawaty Wangsa, and Ernesto Damiani. "The future of E-learning: E-learning ecosystem." In *2007 inaugural IEEE-IES digital ecosystems and technologies conference*, pp. 113-117. IEEE, 2007.

[16]. Uden, Lorna, Ince Trisnawaty Wangsa, and Ernesto Damiani. "The future of E-learning: E-learning ecosystem." In *2007 inaugural IEEE-IES digital ecosystems and technologies conference*, pp. 113-117. IEEE, 2007.

[17]. Blake, Holly. "Staff perceptions of e-learning for teaching delivery in healthcare." *Learning in Health and Social Care* 8, no. 3 (2009): 223-234.

[18]. Anghel, Mariana, and Vasile Ciocodeică. "THE INTELLECTUALS'OPINION REGARDING THE INTEGRATION OF ROMANIA INTO THE EUROPEAN UNION." *Annals of the University of Petroşani* 10, no. 2 (2010): 5-12.

[19]. Schweizer, Heidi. "E-learning in business." *Journal of management education* 28, no. 6 (2004): 674-692.

[20]. Fryer, Luke K., and H. Nicholas Bovee. "Supporting students' motivation for e-learning: Teachers matter on and offline." *The Internet and Higher Education* 30 (2016): 21-29.

[21]. Alshamsi, Aysha Meshaal, Hadeel El-Kassabi, Mohamed Adel Serhani, and Chafik Bouhaddioui. "A multi-criteria decision-making (MCDM) approach for data-driven distance learning recommendations." *Education and Information Technologies* 28, no. 8 (2023): 10421-10458.

[22]. Ma, Jiwei, Zihui Zhu, and Xiaoshuang Liu. "RETRACTED ARTICLE: Assessing the impact of information technology on modern learning approaches: AHP and TOPSIS analysis of blended, flipped, and E-learning." *Soft Computing* 28, no. Suppl 2 (2024): 613-613.

[23]. Naveed, Quadri Noorulhasan, Mohamed Rafik Noor Qureshi, Nasser Tairan, AbdulHafeez Mohammad, Asadullah Shaikh, Alhuseen O. Alsayed, Asadullah Shah, and Fahad Mazaed Alotaibi. "Evaluating critical success factors in implementing E-learning system using multi-criteria decision-making." *Plos one* 15, no. 5 (2020): e0231465.

[24]. Ahmad, Tashfeen. "Scenario based approach to re-imagining future of higher education which prepares students for the future of work." *Higher Education, Skills and Work-Based Learning* 10, no. 1 (2020): 217-238.

[25]. Çelikbilek, Yakup, and Ayşe Nur Adıgüzel Tüylü. "Prioritizing the components of e-learning systems by using fuzzy DEMATEL and ANP." *Interactive Learning Environments* 30, no. 2 (2022): 322-343.

[26]. Xu, Xiuqin, Jialiang Xie, Honghui Wang, and Mingwei Lin. "RETRACTED ARTICLE: Online education satisfaction assessment based on cloud model and fuzzy TOPSIS." *Applied Intelligence* 52, no. 12 (2022): 13659-13674.

[27]. Ince, M., T. Yigit, and A. H. Isik. "AHP-TOPSIS method for learning object metadata evaluation." *Int. J. Inf. Educ. Technol* 7, no. 12 (2017): 884-887.

[28]. Hii, Puong Koh, Chin Fei Goh, Amran Rasli, and Owee Kowang Tan. "A Review of Two Decades of Research on the Application of Multicriteria Decision Making Techniques to Evaluate e-Learning's Effectiveness." *Knowledge Management & E-Learning* 14, no. 4 (2022): 466-488.

[29]. Atıcı, Uğur, Aylin Adem, Mehmet Burak Şenol, and Metin Dağdeviren. "A comprehensive decision framework with interval valued type-2 fuzzy AHP for evaluating all critical success factors of e-learning platforms." *Education and information technologies* 27, no. 5 (2022): 5989-6014.

[30]. Ouatik, Farouk, Mohammed Erritali, Fahd Ouatik, and Mostafa Jourhmane. "Student orientation recommender system using topsis and ahp." *Journal of Information and Organizational Sciences* 46, no. 2 (2022): 473-489.

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