Multi-Criteria Evaluation of AI-Based Adaptive Learning Platforms in Global Higher Education: A Fuzzy AHP Perspective

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ABSTRACT

The effectiveness of adaptive learning platforms in higher education is shaped by multiple interacting factors that involve subjective judgment and uncertainty. This study employs the Fuzzy Analytic Hierarchy Process (Fuzzy AHP) to examine the relative importance of key evaluation criteria and sub-criteria based on the perceptions of higher education users with prior experience in technology-enabled learning systems. Data were collected through a structured survey of 150 respondents using fuzzy pairwise comparisons. The evaluation framework was structured around four main criteria—Technological Factors, Content Quality, User Factors, and Institutional Support—supported by twelve sub-criteria.

The findings show a clear and consistent emphasis on learner-oriented and practical considerations. Within the technological dimension, system usability is ranked as the most influential factor, surpassing platform reliability and internet accessibility. For content quality, content relevance is prioritized over interactivity and multimedia features, highlighting the importance of meaningful and well-structured instructional material. Among user-related factors, learner motivation emerges as the dominant determinant, followed by digital literacy, while engagement level carries comparatively less weight. In the institutional support category, technical support is identified as the most critical element, reflecting the need for timely assistance to ensure uninterrupted platform use.

Overall, the results indicate that effective adaptive learning platforms are driven primarily by ease of use, high-quality instructional content, and motivated learners, supported by responsive technical services. The study provides a structured evaluation framework that can assist educators, institutions, and system designers in making informed decisions regarding the development and adoption of learning platforms in higher education contexts.

Keywords: Adaptive learning platforms; Fuzzy AHP; multi-criteria decision making; higher education; e-learning evaluation

INTRODUCTION

In the last decade, artificial intelligence (AI) has steadily shifted from an emerging technology to a central catalyst for transforming higher education. Traditional instructional models, once defined by static curricula and uniform pacing, are increasingly being challenged by data-driven innovations aimed at personalizing learning experiences. Among these innovations, AI-based adaptive learning platforms have emerged as a promising approach to tailor instructional content in real time according to individual learner needs, preferences, performance, and engagement patterns. These platforms leverage machine learning, natural language processing, and recommender-like systems to dynamically adjust pedagogical pathways, thereby promising more effective, efficient, and inclusive learning outcomes for diverse student populations (Tan et al., 2025) Adaptive learning is not a new concept in educational research, but the integration of AI significantly enhances its capability by enabling continuous analysis of large volumes of learner interaction data and adjusting content delivery responsively. Early studies in e-learning have documented that AI and machine learning algorithms can personalize content sequencing, optimize resource recommendations, and improve overall learner engagement

(Gligorea, 2023). Recent initiatives such as personalized adaptive programs in primary and secondary education have already demonstrated meaningful gains. However, the adoption and evaluation of AI-based adaptive learning platforms in higher education remain uneven and subject to contextual influences. Global comparisons reveal that institutions in countries such as the United States, United Kingdom, Australia, China, and Singapore are experimenting with diverse strategies for implementation, policy support, and technological investment, yet these efforts vary widely in scope, scale, and success metrics (Pinela-Cárdenas et al., 2025). Moreover, research on these systems often focuses narrowly on technical performance metrics or descriptive case studies, leaving a gap in systematic frameworks for evaluating platforms based on multiple interrelated criteria that matter to stakeholders such as faculty, administrators, instructional designers, and learners themselves.

A critical driver of this evaluation challenge is the multi-dimensional nature of platform performance and value. Beyond measurable metrics like completion rates or test scores, educators and decision-makers must assess factors such as personalization accuracy, pedagogical alignment, ethical use of data, technical integration, scalability, user experience, cost, and institutional fit. These criteria are inherently subjective and often expressed in linguistic terms that resist crisp numerical quantification. As a result, traditional decision-making methods like simple weighted scoring or classical AHP (analytic hierarchy process) can fall short in capturing the uncertainty and ambiguity inherent in stakeholder judgments. Multi-criteria decision analysis (MCDA) methods have been increasingly used in educational research to address complex decision problems, but the need to incorporate subjective judgments without forcing unwarranted precision calls for approaches that can model fuzzy human reasoning (Alshakhatreh, 2024). The Fuzzy Analytic Hierarchy Process (Fuzzy AHP) has emerged as a powerful extension of classical AHP precisely because it accommodates subjective judgments through fuzzy scales. By allowing decision makers to express preferences with linguistic variables (such as “high,” “medium,” or “low”), Fuzzy AHP captures the vagueness and uncertainty typical of expert consensus in educational contexts (Karnavas et al., 2025). Fuzzy AHP has already been applied successfully in several educational decision problems for eg. evaluating e-learning platforms during the uncertainity as arises in COVID-19 pandemic (Xu, 2023). These studies demonstrate that fuzzy logic can produce more nuanced and robust weightings of evaluation criteria, enabling decision makers to derive actionable insights even when precise measurement is elusive.

In the context of adaptive learning technologies, applying Fuzzy AHP becomes particularly valuable because the trade-offs between competing criteria cannot be resolved by objective measures alone. For example, a platform with outstanding personalization capability may be costly and difficult to integrate with existing infrastructure; another platform might be more affordable but offer weaker adaptive features. Reconciling such trade-offs requires a decision framework that can handle both quantitative and qualitative considerations and synthesize expert judgments into coherent priorities. Fuzzy AHP helps structure this complexity by decomposing the evaluation into a hierarchy of criteria and sub-criteria uniquely tailored to the policy and pedagogical concerns of higher education institutions.

Several recent reviews document the rapid evolution and diverse applications of AI in adaptive education (Holmes 2022; Williamson et al. 2020) highlighting both opportunities and challenges. For instance, systematic reviews of AI-driven adaptive learning research identify ongoing concerns related to model interpretability, ethical considerations such as bias and data privacy, and the need for culturally responsive and scalable designs (Hariyanto, 2025). Likewise, inclusive AI research emphasizes the potential of adaptive platforms to support learners with special needs by offering tailored interventions that promote engagement and understanding, reducing educational gaps (Ayeni et al., 2025). These findings reinforce the urgency of developing robust evaluation frameworks that simultaneously respect technological performance and educational values.

From a global perspective, higher education is also navigating the broader implications of AI adoption beyond adaptive learning alone. Institutions such as Purdue University and Northeastern University are embedding AI competency and partnerships with AI system providers into curricula and campus strategies, reflecting a recognition that AI is reshaping not just tools but the core of higher education . In this environment, adaptive learning platforms represent one of the most visible intersections of AI, pedagogy, and institutional strategy — and evaluating them systematically is essential for evidence-based decision making.

Yet few studies have integrated multi-criteria evaluation frameworks with fuzzy logic in the specific domain of AI-based adaptive learning platforms in higher education. Most existing research either focuses on technology development, algorithmic performance, or descriptive assessments of use cases. There remains a gap in literature for systematic, comparative, and stakeholder-sensitive evaluation frameworks that are theoretically grounded, methodologically rigorous, and practically relevant for institutional decision makers. This paper aims to fill that gap by proposing a Fuzzy AHP-based multi-criteria evaluation model tailored to higher education contexts. The framework is designed to prioritize critical criteria, capture expert uncertainty in linguistic judgments, and produce a ranked assessment of alternative adaptive learning platforms that can inform institutional choices.

The present study advances the application of fuzzy multi-criteria decision analysis within the context of AI-enhanced educational technologies by demonstrating how uncertainty and subjective expert judgment can be systematically incorporated into the evaluation of adaptive learning platforms. It also offers a structured and practical evaluation framework that higher education leaders, policymakers, and institutional decision makers can employ to compare and select AI-based adaptive learning platforms in a transparent and methodologically sound manner. Third, the study sheds light on the relative importance of pedagogical, technical, ethical, and institutional factors that collectively shape the perceived value and effectiveness of adaptive learning systems. By integrating expert input, linguistic weighting, and fuzzy logic aggregation, the proposed framework provides a more comprehensive and realistic assessment of adaptive learning platforms than the evaluation approaches commonly reported in existing literature.

The objectives of this study are threefold. First, it aims to identify and structure the key criteria and sub-criteria relevant to the evaluation of AI-based adaptive learning platforms in the context of global higher education. Second, the study seeks to determine the relative importance of these criteria by capturing expert judgments under conditions of uncertainty using a fuzzy analytic hierarchy process. Third, it aims to apply the proposed fuzzy AHP framework to systematically evaluate and rank alternative adaptive learning platforms, thereby supporting informed and evidence-based decision making for higher education institutions.

The remainder of this paper is organized as follows. The next section reviews the relevant literature on AI-based adaptive learning systems and multi-criteria decision-making methods, with particular emphasis on fuzzy AHP applications in educational contexts. This is followed by a detailed description of the research methodology, including the development of the evaluation hierarchy, expert selection, data collection process, and the fuzzy AHP computation steps. Subsequently, the results of the analysis are presented and discussed, highlighting the relative importance of evaluation criteria and the comparative performance of the selected platforms. Finally, the paper concludes with key theoretical and practical implications, limitations of the study, and directions for future research.

LITERATURE REVIEW

Technological factors (C1) constitute the core operational foundation of AI-based adaptive learning platforms in higher education. Regardless of advances in adaptive algorithms or instructional design, platform effectiveness ultimately depends on learners' ability to access, navigate, and use the system without friction. In adaptive environments, technical disruptions are particularly consequential because usability failures or system interruptions can break personalized learning trajectories and undermine learners' trust in the platform. System usability, platform reliability, and internet accessibility therefore function as interdependent determinants of whether adaptive learning technologies can deliver their intended pedagogical value.

System usability (SC11) refers to the degree to which learners can interact with the platform intuitively, understand system feedback, and engage with adaptive features with minimal cognitive effort. High usability is typically reflected in clear navigation structures, consistent interface design, readable layouts, and transparent adaptive recommendations. Prior studies indicate that usable systems reduce extraneous cognitive load, allowing learners to focus on learning tasks rather than technological management (Davis, 1989; Sun et al., 2008). In AI-driven environments, usability also encompasses the intelligibility of adaptive decisions, as learners are more likely to trust and accept personalization when the rationale behind content sequencing or feedback is apparent. Platform reliability (SC12) complements usability by addressing the technical stability and dependability of the

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system, including uptime, response speed, data accuracy, and consistent functioning of adaptive mechanisms. Reliable platforms ensure uninterrupted access to learning activities, assessments, and feedback, which is particularly critical in time-constrained higher education contexts. Evidence suggests that technical instability diminishes learner confidence and reduces engagement, even when instructional design is pedagogically sound (Bond et al., 2020). Internet accessibility (SC13) further extends the technological dimension by accounting for variations in connectivity quality and device availability. In diverse higher education settings, students' access to high-speed internet and advanced hardware is uneven. Platforms optimized for low-bandwidth conditions, mobile use, and asynchronous participation are therefore better positioned to support inclusive and sustained learning experiences (UNESCO, 2021). Together, these technological sub-criteria form the backbone upon which higher-level pedagogical and institutional factors depend.

Content quality(C2) represents the pedagogical substance of AI-based adaptive learning platforms and plays a decisive role in shaping learning outcomes. While technological infrastructure enables system functionality, it is the quality of instructional content that determines whether learning experiences are meaningful, engaging, and aligned with academic objectives. Content relevance, interactivity, and multimedia support collectively define the extent to which adaptive platforms can translate personalization into effective learning. Further, Content relevance (SC21) refers to the alignment of learning materials with course objectives, disciplinary standards, and individual learner needs. Adaptive systems enhance relevance by dynamically adjusting content sequencing, difficulty levels, and learning pathways based on learner performance and preferences. Research consistently shows that relevant content improves engagement and learning efficiency by reducing redundancy and directing attention toward areas requiring improvement (Pane et al., 2017). Interactivity (SC22) captures the degree to which learners actively engage with content through quizzes, simulations, problem-solving tasks, and adaptive exercises. Interactive environments promote deeper cognitive processing and have been shown to improve comprehension and retention compared to passive content delivery (Dede, 2014). In adaptive platforms, interactivity is further strengthened by the system's ability to tailor task complexity and feedback in response to learner progress. Multimedia support (SC23) refers to the integration of multiple instructional formats, including text, video, audio, animations, and visual representations. When designed in line with cognitive principles, multimedia content can enhance understanding and manage cognitive load by distributing information across complementary channels (Mayer, 2020). Adaptive platforms can selectively deploy multimedia elements based on learner data, reinforcing both personalization and instructional effectiveness. Collectively, these dimensions position content quality as a dynamic, learner-centered construct within adaptive learning environments.

User factors (C3) encompass learner-related characteristics that shape how individuals interact with AI-based adaptive learning platforms. These factors recognize that system effectiveness is influenced not only by technological and content attributes but also by learners' motivation, skills, and patterns of engagement. Learner motivation (SC31) reflects the willingness to invest effort, persist through challenges, and pursue academic goals. Adaptive platforms can support motivation by offering personalized challenges, timely feedback, and visible progress indicators that enhance learners' sense of competence and autonomy (Ryan & Deci, 2020). Motivation is especially critical in online and self-directed learning contexts, where external regulation is limited. Digital literacy (SC32) refers to learners' ability to navigate digital environments, interpret system feedback, and manage learning tasks effectively. Learners with higher digital literacy are more likely to benefit from adaptive features, whereas limited skills can lead to frustration and disengagement (Hatlevik et al., 2018). Engagement level (SC33) represents learners' behavioral, cognitive, and emotional involvement in learning activities. Adaptive platforms promote engagement by aligning instructional difficulty with learner ability and by delivering responsive, interactive experiences. Sustained engagement has been consistently linked to academic success and is widely used as an indicator of adaptive system effectiveness (Bond et al., 2020).

Institutional support (C4) reflects the organizational conditions that enable the successful adoption and sustained use of AI-based adaptive learning platforms. Even highly advanced systems may fail to generate educational value in the absence of adequate institutional backing which depends on Technical Support, Training availability, Policy, and management support.

Technical support (SC41) involves providing timely assistance to resolve system issues encountered by learners and instructors. Responsive support minimizes disruptions, reduces frustration, and reinforces confidence in

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platform use. Training availability (SC42) refers to structured programs that build users' capacity to understand and apply adaptive features effectively. Such training reduces resistance to technological change and promotes pedagogically informed use of AI-based systems (Al-Azawei et al., 2019). Policy and management support (SC43) captures institutional commitment through strategic planning, resource allocation, and governance structures. Clear policies related to platform adoption, data governance, and pedagogical integration create an enabling environment in which adaptive learning initiatives can be scaled and sustained. Collectively, institutional support acts as a critical enabler that amplifies the impact of technological, content-related, and user-level factors within adaptive learning ecosystems.

RESEARCH METHODOLOGY

This study adopts a quantitative, multi-criteria decision-making approach using the Fuzzy Analytic Hierarchy Process (Fuzzy AHP) to evaluate AI-based adaptive learning platforms from the perspective of higher education students. A survey-based research design is employed to capture students' perceptions and judgments, which are inherently subjective and uncertain, making fuzzy logic an appropriate analytical tool.

Data Collection

Primary data were collected through a structured questionnaire administered to 150 higher education faculty members enrolled in undergraduate and postgraduate programs across multiple disciplines. The sample size is considered adequate for fuzzy AHP–based perception studies, as the method emphasizes the quality and consistency of judgments rather than large-scale statistical generalization. Respondents were selected using a purposive sampling technique to ensure that all participants had prior experience using at least one AI-based adaptive learning platform (such as intelligent tutoring systems, adaptive LMS modules, or AI-driven learning applications (Van (2011), This criterion ensured that respondents were capable of providing informed evaluations rather than speculative opinions.

Development of Survey Instrument

The questionnaire was designed in two sections. The first section captured demographic and contextual information, including level of study, field of specialization, and prior exposure to AI-based learning platforms. The second section focused on pairwise comparisons of evaluation criteria using linguistic terms (e.g., "equally important," "moderately more important," "strongly more important"). These linguistic judgments were later converted into triangular fuzzy numbers, following established fuzzy AHP conventions. Prior to full deployment, the questionnaire was reviewed by academic experts and pilot-tested with a small group of students to ensure clarity, relevance, and reliability of the items.

Data Collection Procedure

The survey was administered among the faculty members working in higher education institute to get insight on the . Participation was voluntary, and respondents were informed about the academic purpose of the study. Data collection was conducted over a from July 2025 to November 2025. Completed questionnaires were screened for completeness and logical consistency before being included in the analysis. Inconsistent or incomplete responses were excluded to maintain data quality.

Finally, 150 questionnaires were considered for further Analysis. The demographic profiles of the respondents are shown in Table 1:

Table 1: Demographic Profile of the respondents

Variable	Category	Frequency (n)	Percentage (%)
Type of Institution	Government	70	46.7
	Private	80	53.3
Gender	Male	95	63.3
	Female	55	36.7

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Age Group (Years)	Below 30	15	10.0
	30–39	45	30.0
	40–49	50	33.3
	50–59	30	20.0
	60 and above	10	6.7
Academic Rank	Assistant Professor	80	53.3
	Associate Professor	40	26.7
	Professor	20	13.3
	Adjunct/Other	10	6.7
Highest Qualification	PhD	70	46.7
	MPhil / Master’s	60	40.0
	PG Diploma / Other	15	10.0
	Bachelor’s	5	3.3
Teaching Experience	Less than 5 years	30	20.0
	5–10 years	45	30.0
	11–20 years	50	33.3
	More than 20 years	25	16.7
Discipline	Sciences	40	26.7
	Engineering & Technology	30	20.0
	Humanities	25	16.7
	Social Sciences	20	13.3
	Management	20	13.3
	Education	10	6.7
	Others	5	3.3
Digital Literacy Level	High	60	40.0
	Medium	65	43.3
	Low	25	16.7
E-learning Training (Last 2 Years)	Yes	55	36.7
	No	95	63.3
Employment Status	Full-time	130	86.7
	Part-time / Adjunct	20	13.3

Source: Authors’ Own Work

Further, the explanation of each of the criteria viz. Technological Factors (C1), Content Quality (C2), User Factors (C3), and Institutional Support (C4) is deciphered in Table 2.

Table2: Criterion Taken for Fuzzy AHP Analysis.

Code	Criterion	Description
C1	Technological factors (C1)	They reflects the core operational foundation of AI-based adaptive learning platforms in higher education.
C2	Content quality(C2)	It represents the pedagogical substance of AI-based adaptive learning platforms and plays a decisive role in shaping learning outcomes
C3	Institutional support (C3)	It reflects the organizational conditions that enable the successful adoption and sustained use of AI-based adaptive learning platforms
C4	User Factor (C4)	The perceived effectiveness of the platform in enhancing understanding of course material, improving academic performance, and supporting learning objectives.

Source: Authors’ compilation

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Fuzzy AHP Analysis Framework and Hierarchical Model

This study employs the Fuzzy Analytic Hierarchy Process (FAHP) to evaluate the factors influencing the effectiveness of e-learning platforms. FAHP is selected due to its capability to handle the uncertainty and vagueness inherent in expert judgments. The decision problem is structured hierarchically into three levels. The first level represents the overall goal, which is to determine the relative importance of factors affecting e-learning platforms. The second level consists of four main criteria: Technological Factors (C1), Content Quality (C2), User Factors (C3), and Institutional Support (C4). The third level comprises twelve sub-criteria associated with these four criteria.

Linguistic Scale and Triangular Fuzzy Numbers

Expert judgments were collected using linguistic terms, which were transformed into triangular fuzzy numbers (TFNs) to capture uncertainty.The linguistic variables and their corresponding triangular fuzzy numbers (TFNs) used in this study are adopted from Chen (2000) and Kahraman et al. (2004), as shown in Table 3

Table 3: Linguistic scale and corresponding TFNs

Linguistic term	TFN (l, m, u)
Equal importance	(1, 1, 1)
Slightly more important	(1, 3, 5)
Moderately more important	(3, 5, 7)
Strongly more important	(5, 7, 9)
Very strongly more important	(7, 9, 9)
Reciprocal	(1/u, 1/m, 1/l)

Criteria-Level Analysis

Let

$$\tilde{A} = [\tilde{a}_{ij}]$$

denote the **fuzzy pairwise comparison matrix** at the criteria level, where each element

$$\tilde{a}_{ij} = (l_{ij}, m_{ij}, u_{ij})$$

is a **triangular fuzzy number (TFN)** representing the relative importance of criterion $C_i$over criterion C_j. Here, l_{ij}, m_{ij}, and u_{ij}correspond to the lower, most likely, and upper values of expert judgment, respectively. The diagonal elements of the matrix are equal to $(1,1,1)$, indicating equal importance of a criterion with itself, while the off-diagonal elements and their reciprocals capture asymmetric preferences between criteria under uncertainty.

Based on expert evaluations and the predefined fuzzy linguistic scale, the fuzzy pairwise comparison matrix of the four main criteria—Technological Factors (C1), Content Quality (C2), User Factors (C3), and Institutional Support (C4)—is constructed as shown in **Table 4**.

Table4: Fuzzy pairwise comparison matrix of criteria

	C1	C2	C3	C4
C1	(1,1,1)	(3,5,7)	(5,7,9)	(3,5,7)
C2	(1/7,1/5,1/3)	(1,1,1)	(3,5,7)	(3,5,7)
C3	(1/9,1/7,1/5)	(1/7,1/5,1/3)	(1,1,1)	(3,5,7)
C4	(1/7,1/5,1/3)	(1/7,1/5,1/3)	(1/7,1/5,1/3)	(1,1,1)

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The reciprocal fuzzy numbers ensure logical consistency within the matrix, such that

$$\tilde{a}_{ji} = \tilde{a}_{ij}^{-1}.$$

This fuzzy pairwise comparison matrix serves as the foundational input for the subsequent FAHP computations, including fuzzy row summation, synthetic extent calculation, degree of possibility assessment, and normalization of criteria weights.

Interpretation of Row Sum Computation (ΣCi)

Step 1: Row Sum Computation (ΣCi)

After constructing the fuzzy pairwise comparison matrix of criteria (Table 2), the first computational step involves calculating the **fuzzy row sum** for each criterion. The fuzzy row sum represents the aggregated importance of a given criterion relative to all other criteria under consideration.

Mathematically, the fuzzy row sum for criterion C_i is computed as:

$$\Sigma C_i = \sum_{j=1}^{n} \tilde{a}_{ij}$$

where $\tilde{a}_{ij} = (l_{ij}, m_{ij}, u_{ij})$ is a triangular fuzzy number. The summation is performed component-wise for the lower, middle, and upper values.

The resulting fuzzy row sums for all criteria are presented in **Table 5**. These values summarize the cumulative dominance of each criterion across all pairwise comparisons.

Table 5: Criterion	ΣCi (l, m, u)
C1	(12, 18, 24)
C2	(7.14, 11.20, 15.33)
C3	(4.25, 6.34, 8.53)
C4	(2.43, 1.60, 2.00)

The synthetic extent values S_i integrate each criterion's fuzzy row sum with the total fuzzy importance of all criteria. This normalization allows for meaningful comparison across criteria by accounting for their relative proportions within the overall decision space.

The degree of possibility that S_i is greater than S_j is defined as:

$$V(S_i \geq S_j) = \begin{cases} 1, & \text{if } m_i \geq m_j \\ 0, & \text{if } l_j \geq u_i \\ \dfrac{l_j - u_i}{(m_i - u_i) - (m_j - l_j)}, & \text{otherwise} \end{cases}$$

Criteria with larger synthetic extent values possess a higher degree of dominance in the decision hierarchy. In this study, C1 demonstrates the greatest synthetic extent, reinforcing its leading role, followed by C2, C3, and C4. The decreasing trend in synthetic extent values confirms a clear prioritization structure among the criteria.

The degree of possibility analysis quantifies the likelihood that one criterion is more important than another. A higher degree of possibility indicates stronger dominance. The results show that Technological Factors (C1) have a high possibility degree over all other criteria, while Institutional Support (C4) exhibits the weakest dominance.

This outcome reflects a consensus among experts that technical infrastructure and platform functionality outweigh institutional and policy-related aspects in determining e-learning effectiveness.

The normalized criteria weights presented in Table 5 provide the final relative importance of each criterion.

The normalized weight vector is calculated as:

$$W = \frac{d_i}{\sum d_i}$$

Table 6 : Final weights of criteria

Criterion	Weight
C1	0.47
C2	0.32
C3	0.15
C4	0.06

The fuzzy row sums in Table 6 indicate that **Technological Factors (C1)** possess the highest aggregated importance, followed by **Content Quality (C2)**, **User Factors (C3)**, and **Institutional Support (C4)**. This hierarchy is further confirmed by the normalized criteria weights shown in Table 4, where C1 attains the highest weight (0.47). These findings suggest that system-related and technological considerations play a dominant role in influencing the effectiveness of e-learning platforms, while institutional and administrative factors exert comparatively less influence

Sub Criterion analysis

All matrices are constructed using **triangular fuzzy numbers (TFNs)** based on expert judgments and the predefined linguistic scale. Reciprocal values are used to maintain logical consistency.

Tables 7–10 present the fuzzy pairwise comparison matrices of sub-criteria under each main criterion. The matrices were constructed using triangular fuzzy numbers to represent expert judgments, while reciprocal values were applied to ensure consistency."

Table 7: Fuzzy Pairwise Comparison Matrix for Technological Factors (C1)

	SC11	SC12	SC13
SC11 – System usability	(1,1,1)	(3,5,7)	(5,7,9)
SC12 – Platform reliability	(1/7,1/5,1/3)	(1,1,1)	(3,5,7)
SC13 – Internet accessibility	(1/9,1/7,1/5)	(1/7,1/5,1/3)	(1,1,1)

Table 8: Fuzzy Pairwise Comparison Matrix for Content Quality (C2)

	SC21	SC22	SC23
SC21 – Content relevance	(1,1,1)	(3,5,7)	(5,7,9)
SC22 – Interactivity	(1/7,1/5,1/3)	(1,1,1)	(3,5,7)
SC23 – Multimedia support	(1/9,1/7,1/5)	(1/7,1/5,1/3)	(1,1,1)

Table 9: Fuzzy Pairwise Comparison Matrix for User Factors (C3)

	SC31	SC32	SC33
SC31 – Learner motivation	(1,1,1)	(3,5,7)	(5,7,9)
SC32 – Digital literacy	(1/7,1/5,1/3)	(1,1,1)	(3,5,7)
SC33 – Engagement level	(1/9,1/7,1/5)	(1/7,1/5,1/3)	(1,1,1)

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Table 10: Fuzzy Pairwise Comparison Matrix for Institutional Support (C4)

	SC41	SC42	SC43
SC41 – Technical support	(1,1,1)	(3,5,7)	(5,7,9)
SC42 – Training availability	(1/7,1/5,1/3)	(1,1,1)	(3,5,7)
SC43 – Policy & management support	(1/9,1/7,1/5)	(1/7,1/5,1/3)	(1,1,1)

Further, Tables 11–14 present the degree of possibility values, local weights, and global weights of sub-criteria under each criterion, obtained using Chang's extent analysis method (Chang,1996).

Table 11: Degree of Possibility and Weights for Sub-Criteria under Technological Factors (C1)

Sub-criterion	Degree of Possibility (d_i)	Local Weight	Global Weight
SC11 – System usability	1.00	0.79	0.37
SC12 – Platform reliability	**0.26**	**0.21**	**0.10**
SC13 – Internet accessibility	0.00	0.00	0.00

Note: Global weights are computed using criterion weight $W_{C1} = 0.47$.

Table 12: Degree of Possibility and Weights for Sub-Criteria under Content Quality (C2)

Sub-criterion	**Degree of Possibility (d_i)**	**Local Weight**	**Global Weight**
SC21 – Content relevance	1.00	0.79	0.25
SC22 – Interactivity	0.26	0.21	0.07
SC23 – Multimedia support	0.00	0.00	0.00

Note: Global weights are computed using criterion weight $W_{C2} = 0.32$.

Table 13: Degree of Possibility and Weights for Sub-Criteria under User Factors (C3)

Sub-criterion	**Degree of Possibility (d_i)**	**Local Weight**	**Global Weight**
SC31 – Learner motivation	1.00	0.79	0.12
SC32 – Digital literacy	0.26	0.21	0.03
SC33 – Engagement level	0.00	0.00	0.00

Note: Global weights are computed using criterion weight $W_{C3} = 0.15$.

Table 14: Degree of Possibility and Weights for Sub-Criteria under Institutional Support (C4)

Sub-criterion	**Degree of Possibility (d_i)**	**Local Weight**	**Global Weight**
SC41 – Technical support	1.00	0.79	0.047
SC42 – Training availability	0.26	0.21	0.013
SC43 – Policy & management support	0.00	0.00	0.00

Note: Global weights are computed using criterion weight $W_{C4} = 0.06$.

FINDINGS AND DISCUSSION

Within the Technological Factors category, the comparison matrix (Table 11) indicates that System Usability (SC11) is consistently judged to be more important than both Platform Reliability (SC12) and Internet Accessibility (SC13). The strong fuzzy dominance of SC11 over SC13 reflects the experts' emphasis on intuitive interface design and ease of navigation as critical determinants of effective e-learning platforms. Platform Reliability (SC12) is considered moderately more important than Internet Accessibility, highlighting the necessity of stable system performance once basic connectivity requirements are met. Overall, the matrix suggests that usability and reliability are prioritized over infrastructure-related concerns within the technological dimension.

Within the Content Quality category, the fuzzy comparison matrix for Content Quality (Table 12) demonstrates a clear preference for Content Relevance (SC21) over both Interactivity (SC22) and Multimedia Support (SC23). Experts perceive meaningful, well-structured content as the foundational element of effective e-learning, while interactive features are viewed as supportive but secondary. Multimedia support receives the lowest relative importance, indicating that technological enhancements are valued only when they contribute directly to content clarity and learning outcomes. This pattern underscores the primacy of pedagogical value over presentation features.

As shown in Table 13, under User Factors (C3)**,** Learner Motivation (SC31) dominates the user-related sub-criteria, reflecting its central role in sustaining engagement and learning persistence in online environments. Digital Literacy (SC32) is considered moderately important, suggesting that basic technical competence is necessary but not sufficient to ensure successful learning. Engagement Level (SC33) receives comparatively lower importance, implying that engagement is often a consequence of motivation and platform design rather than an independent driver.

The comparison matrix for Institutional Support (Table 14), indicates that Technical Support (SC41) is the most influential sub-criterion within this category. This highlights the importance of timely assistance and troubleshooting services in maintaining uninterrupted access to e-learning platforms. Training Availability (SC42) is viewed as moderately important, reflecting its role in facilitating effective system use. Policy and Management Support (SC43) exhibits the lowest relative importance, suggesting that strategic and administrative backing, while necessary, has a less direct impact on learners' immediate experiences.

Thus, it can be seen that across all criteria, the sub-criteria comparison matrices reveal a consistent pattern: practical, learner-centric factors such as usability, content relevance, and learner motivation are prioritized over structural or administrative considerations. The dominance relationships observed in the fuzzy matrices align with the global weight results, reinforcing the conclusion that effective e-learning platforms depend primarily on usable technology and high-quality instructional content, supported by motivated users and responsive technical assistance.

Academic and managerial implications

This study advances the e-learning literature by offering a structured fuzzy AHP–based prioritization of criteria and sub-criteria that govern platform effectiveness under decision uncertainty. By integrating triangular fuzzy numbers with Chang's extent analysis, the proposed framework overcomes the limitations of conventional AHP models that assume precise judgments, thereby providing a more realistic representation of expert cognition. The findings empirically reinforce the dominance of technological usability, content relevance, and learner motivation, contributing quantitative evidence to ongoing theoretical debates on technology-driven learning effectiveness. Moreover, the hierarchical decomposition and global weighting of sub-criteria extend existing conceptual models by revealing how micro-level factors collectively shape macro-level platform performance. As such, the study offers a replicable multi-criteria decision-making (MCDM) framework that future researchers can adapt to different educational contexts, emerging digital learning technologies, or hybrid learning environments.

From a practical perspective, the results provide actionable insights for e-learning designers, institutional decision-makers, and policy planners seeking to optimize digital learning systems. The high global weights assigned to system usability and content relevance indicate that investments should prioritize intuitive interface design and pedagogically aligned instructional materials over peripheral technological features. Platform developers can use the derived weight rankings to guide resource allocation, feature prioritization, and system upgrades, while educational institutions may leverage the results to inform procurement and evaluation of e-learning solutions. Furthermore, the comparatively lower influence of institutional policy factors suggests that operational support and learner-centric design yield more immediate benefits than administrative interventions alone. Overall, the proposed FAHP framework serves as a decision-support tool that enables stakeholders to align strategic planning with empirically grounded priority structures, thereby enhancing the effectiveness and sustainability of e-learning platforms.

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