Article history:
Received 20 March 2024
Revised 20 May 2024
Accepted 24 May 2024
Published online 01 June 2024

Journal of Resource Management and Decision Engineering

Volume 3, Issue 2, pp 1-12

Design of a Fuzzy Expert System for Measuring the Satisfaction of E-Mathematics Learners (Case Study: Farhangian University of Mazandaran)

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Article Info

Article type:
Original Research

How to cite this article:
Gorzinnezhad, M. , Dehghandar, M. & Darvishi Salookolaei, D. (2024). Design of a Fuzzy Expert System for Measuring the Satisfaction of E-Mathematics Learners (Case Study: Farhangian University of Mazandaran). *Journal of Resource Management and Decision Engineering, 3*(2), 1-1.
https://doi.org/10.61838/kman.jrmde.3.2.172

ABSTRACT

The issue of student satisfaction with e-learning systems plays a critical role in their academic performance as well as in the success and effectiveness of this educational domain. In this study, a fuzzy expert system was designed using MATLAB software to measure the satisfaction level of e-mathematics learners at Farhangian University of Mazandaran. This fuzzy expert system included four input variables—technical quality of the system and technological infrastructure, educational quality, information and content quality, and service quality—extracted from the theoretical literature of the study; one output variable—e-mathematics learner satisfaction; trapezoidal and triangular membership functions; 50 rules developed based on the input of eight purposively selected experts from Farhangian University; and the centroid defuzzification method. All input and output variables of this system were normalized and converted to a range between 0 and 1, and using the input values, satisfaction levels were estimated with an error margin of less than 0.15. Considering the strong ability of this fuzzy expert system to estimate the satisfaction of e-learners, and given its design based on criteria, sub-criteria, and their relative importance according to ranking results used as input variables, it can provide significant support to educational system managers by enabling timely tracking of feedback and problems in proportion to their level of importance, thereby increasing the satisfaction of e-mathematics learners.

Keywords: *E-mathematics learners, Satisfaction, Fuzzy expert system, Farhangian University of Mazandaran.*

1. Introduction

The accelerated digital transformation of higher education has positioned e-learning as a strategic imperative for universities worldwide. Over the past two decades, e-learning has evolved from a peripheral instructional method to a mainstream approach that influences educational access, quality, and learner satisfaction (Oulamine et al., 2025; Pei-Chen & Hsing

Kenny, 2025). The rapid adoption of digital technologies has enabled new opportunities for personalized and flexible learning while simultaneously presenting challenges in instructional design, system usability, and quality assurance (Asgari et al., 2023; Seraji & Attaran, 2012). Among various academic disciplines, mathematics remains a critical area where e-learning can both democratize access and address long-standing pedagogical challenges (Jafarabadi Ashtiani & Nomanov, 2021; Ragib, 2023). However, the effectiveness of online mathematics instruction depends not only on content delivery but also on the extent to which learners perceive the system as reliable, engaging, and supportive (Chen & Young Tat Yao, 2016; Yakubu & Dasuki, 2018).

Understanding learner satisfaction within e-learning environments is essential because it serves as a predictor of continued system use, academic performance, and motivation (Maria de Lourdes et al., 2011; Mohammadi, 2015). According to information systems success models, system quality, information quality, and service quality jointly shape user perceptions and acceptance (Chen & Tseng, 2012; Yakubu & Dasuki, 2018). For mathematics, where cognitive load can be high, the integration of interactive and problem-solving elements further influences learners' engagement (Jafarabadi Ashtiani & Nomanov, 2021; Pei-Chen & Hsing Kenny, 2025). Previous studies have shown that when digital platforms are well-designed, with adaptive feedback and clear instructional support, learners report higher satisfaction and improved performance (Zare et al., 2024; Zare et al., 2023). Conversely, systems lacking intuitive design, timely assistance, or relevant content often lead to frustration and disengagement (Cheawjindakarn et al., 2013; Karimzadganmoghadam et al., 2012).

Research in the Iranian higher education context highlights unique factors affecting e-learning quality and satisfaction. Universities such as Farhangian University, which train future educators, have emphasized integrating advanced instructional technologies while maintaining pedagogical rigor (Faraj Elahi et al., 2020; Zare et al., 2024). Studies show that teacher readiness, institutional support, and the adaptability of systems to learners' cognitive and motivational needs are vital in ensuring success (Fazeli et al., 2021; Narenji Thani et al., 2021). In mathematics education specifically, interactive problem-based learning and self-regulated strategies have been identified as mechanisms that enhance learners' confidence and persistence in digital environments (Farhadi, 2015; Poorasghar et al., 2015). Furthermore, localized research has highlighted the importance of system personalization and cultural responsiveness to meet the expectations of Iranian learners (Dehghandar et al., 2020; Gorzin Nezhad et al., 2020).

To measure and improve learner satisfaction effectively, researchers have increasingly adopted intelligent computational approaches. Fuzzy expert systems, in particular, have proven valuable in modeling complex, subjective factors such as satisfaction, where variables may be uncertain or imprecise (Babakordi, 2020; Elahi et al., 2015). Traditional evaluation methods often fail to capture the nuances of human perceptions and the interplay of multiple quality dimensions (Chen & Young Tat Yao, 2016; Filippova, 2015). By contrast, fuzzy logic allows the translation of expert judgments into quantifiable decision rules, providing actionable insights for educational managers (Dehghandar, Ahmadi, et al., 2021; Dehghandar, Pabasteh, et al., 2021). For example, previous applications of fuzzy systems in educational contexts have successfully diagnosed learning barriers, predicted academic performance, and guided policy interventions (Babakordi, 2020; Dehghandar, Pabasteh, et al., 2021).

The e-learning literature identifies four main quality dimensions that shape user satisfaction: system and technological infrastructure, instructional quality, information and content quality, and service quality (Asgari et al., 2023; Cheawjindakarn et al., 2013). System and infrastructure quality encompasses reliability, security, user-friendliness, and flexibility, all critical for reducing technical frustration and cognitive overload (Gorzin Nezhad et al., 2020; Yakubu & Dasuki, 2018). Instructional quality refers to pedagogical design, adaptability to different learning styles, and opportunities for active, collaborative, and problem-based learning (Fazeli et al., 2021; Pei-Chen & Hsing Kenny, 2025). Information and content quality emphasize the accuracy, relevance, comprehensiveness, and timeliness of digital resources (Chen & Young Tat Yao, 2016; Filippova, 2015). Finally, service quality relates to prompt technical support, user feedback integration, and overall responsiveness (Karimzadganmoghadam et al., 2012; Mohammadi, 2015). These dimensions interact dynamically to influence how learners evaluate their educational experience and decide whether to persist with e-learning platforms (Maria de Lourdes et al., 2011; Zare et al., 2023).

Although international studies have investigated these dimensions, there is a recognized gap in applying systematic, data-driven approaches to evaluate e-learner satisfaction within mathematics programs in Iran (Faraj Elahi et al., 2020; Farhadi, 2015). While frameworks like the Technology Acceptance Model (TAM) and the DeLone & McLean model have provided valuable theoretical grounding (Chen & Tseng, 2012; Mohammadi, 2015), their application in highly domain-specific contexts such as mathematics requires additional adaptation (Ragib, 2023). For instance, mathematics students often require interactive content, visualization tools, and adaptive feedback mechanisms that general e-learning systems may lack (Jafarabadi Ashtiani & Nomanov, 2021; Pei-Chen & Hsing Kenny, 2025). Incorporating expert input from faculty specialized in mathematics and educational technology can lead to more precise indicators and evaluation rules (Asgari et al., 2023; Zare et al., 2024).

Moreover, recent advances in artificial intelligence and computational modeling have created opportunities to optimize e-learning platforms proactively (Reis et al., 2024; Sadeghi, 2024). For example, machine learning and fuzzy inference can detect satisfaction trends and signal when interventions are needed to prevent dropout (Babakordi, 2020; Dehghandar, Ahmadi, et al., 2021). The use of fuzzy expert systems enables decision-makers to work with linguistic variables such as “high satisfaction” or “low instructional quality” and convert them into actionable performance indicators (Cheawjindakarn et al., 2013; Elahi et al., 2015). This approach is particularly effective in contexts like Farhangian University, where decision-makers need timely, nuanced feedback to enhance educational technology use and maintain learner motivation (Faraj Elahi et al., 2020; Zare et al., 2024).

Another crucial factor influencing the success of e-learning in mathematics is motivation and self-regulation. Studies suggest that when learners perceive the system as usable, adaptive, and content-rich, they are more likely to adopt effective learning strategies and maintain persistence (Maria de Lourdes et al., 2011; Poorasghar et al., 2015). Active teaching approaches and gamification have also been shown to improve engagement and satisfaction (Fazeli et al., 2021; Sadeghi, 2024). In this sense, evaluating e-learning satisfaction should not be limited to technical infrastructure but should also consider pedagogical strategies that support meaningful learning experiences (Cheawjindakarn et al., 2013; Farhadi, 2015).

Despite the recognized importance of these factors, empirical research focusing on mathematics e-learning satisfaction within teacher education institutions remains scarce. Many evaluation efforts rely on generic survey instruments without integrating expert-based reasoning or multi-criteria analysis (Gorzin Nezhad et al., 2020; Karimzadganmoghadam et al., 2012). This creates a knowledge gap for educational planners seeking actionable insights to refine digital mathematics instruction and align it with student expectations and institutional standards (Asgari et al., 2023; Zare et al., 2023). A robust evaluation model that blends theoretical frameworks with expert-driven fuzzy logic can address this gap by providing a reliable decision-support tool.

The present study responds to this need by designing a fuzzy expert system to evaluate the satisfaction of e-mathematics learners at Farhangian University of Mazandaran. Building on prior work on success factors for e-learning (Cheawjindakarn et al., 2013; Yakubu & Dasuki, 2018) and local research on mathematics e-learning quality (Gorzin Nezhad et al., 2020; Zare et al., 2024), this approach integrates four main quality dimensions—system and technological infrastructure, instructional quality, information and content quality, and service quality—into a coherent measurement model. By leveraging expert knowledge and fuzzy inference, the system addresses the limitations of traditional satisfaction surveys and captures the complex, multi-dimensional nature of learner experience (Babakordi, 2020; Elahi et al., 2015). The outcome provides educational managers with actionable feedback to adjust strategies, improve system usability, and strengthen instructional effectiveness, ultimately leading to higher satisfaction and learning outcomes (Pei-Chen & Hsing Kenny, 2025; Reis et al., 2024).

In sum, the integration of advanced computational methods with established educational quality frameworks offers a promising pathway to enhance e-learning evaluation, particularly in disciplines with high cognitive demands such as mathematics.

2. Methods and Materials

This study is applied–developmental in terms of purpose. The data collection method is survey research. The subject domain of this study relates to the concepts and components of measuring the success of an electronic learning system in the mathematics course, and the geographical domain is Farhangian University of Mazandaran. The data used in this research were collected from Farhangian University.

The statistical population includes all faculty members, experts, and specialists active in e-learning at Farhangian University of Mazandaran. A total of six faculty members from the Department of Mathematics Education and two faculty members from the Department of Educational Technology—each with at least 10 years of academic teaching experience and experience teaching in e-learning environments, as well as publications in the field of e-learning—were purposively selected as experts in accordance with the research objectives.

For this purpose, first, based on a review of the literature, prior research, and the opinions of experts, the key indicators influencing the evaluation of e-learners' success factors were identified and extracted. These criteria were classified into four main dimensions: technical quality of the system and technological infrastructure, educational quality, information and content quality, and service quality.

Finally, to design the fuzzy expert system with four input variables—technical quality of the system and technological infrastructure, educational quality, information and content quality, and service quality—as the main criteria, and one output variable—satisfaction level—as the goal, relevant questionnaires were distributed among the experts, and the results were aggregated. The fuzzy expert system was then designed and developed with these input and output variables and the extracted rules using MATLAB software.

3. Findings and Results

The primary aim of this research was to evaluate and measure the satisfaction of e-learners in the mathematics course at Farhangian University of Mazandaran by designing a fuzzy expert system. Through the examination of reliable scientific sources and a review of similar research activities conducted at domestic and international universities and scientific centers, which were discussed in the introduction and research method sections, four criteria and 24 sub-criteria were ultimately finalized as the main influential factors. These include: (1) technical quality of the system and technological infrastructure, (2) educational quality, (3) information and content quality, and (4) service quality.

The criteria and sub-criteria used are presented in Table 1 as follows.

Table 1

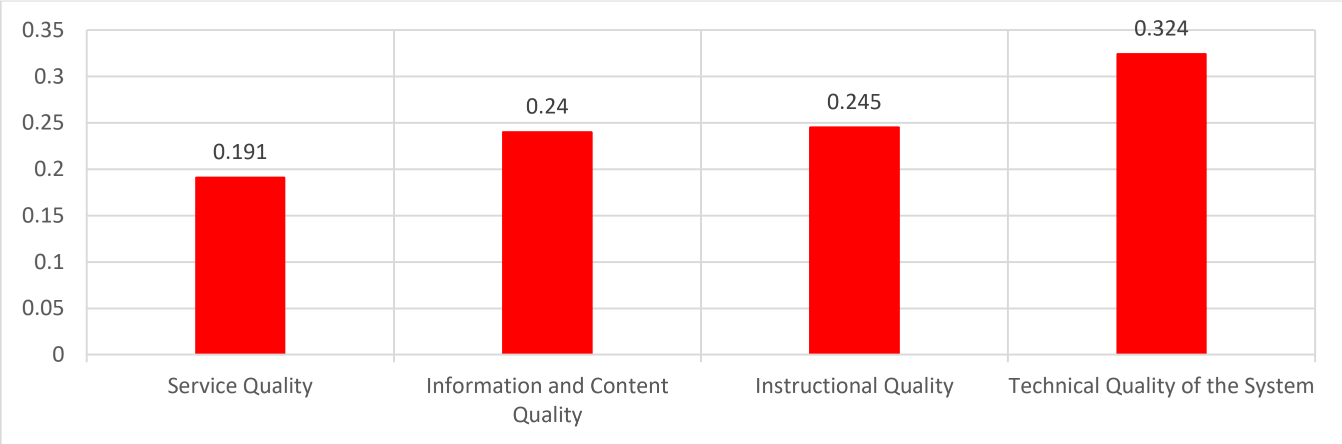
Criteria and Sub-Criteria Used in the Study

Row	Criterion	Sub-Criterion	Sub-Criterion Row
1	Technical Quality of System	System Interactivity	1
		Ease of Access to Online Resources	2
		Ease of Use	3
		User-Friendliness	4
		Degree of Personalization	5
		System Security Assessment	6
		System Flexibility	7
		Structured Design	8
		Communication Capability with Students	9
2	Educational Quality	Organizational Support for Funding and Infrastructure	10
		Compatibility with Various Learning Styles	11
		Performance and Learning Assessment Capability	12
		Collaborative Learning Capability	13
		Needs Assessment and Instructional Design Aligned with Course Goals	14
3	Information & Content Quality	Completeness and Comprehensiveness	15
		Up-to-Date Information and Content	16
		Understandability	17
		Accuracy	18
		Relevance	19
4	Service Quality	Provision of Guidance Services	20
		Timely Responsiveness	21
		Speed of Service Delivery	22
		Course Management	23
		User Feedback Integration	24

By applying the criteria presented in Table 1 and using the fuzzy Analytic Hierarchy Process (FAHP), the weights of the main and sub-criteria were determined, as illustrated in Figure 1.

Figure 1

Weights of Main Criteria for E-Learners' Success



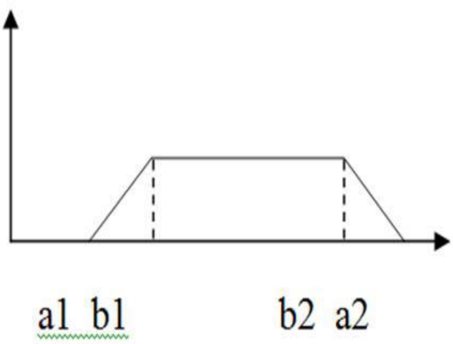
To implement the main process of this study and design the fuzzy expert system, the linguistic variables and triangular and trapezoidal membership functions used are shown in Table 2. It is important to note that all data were normalized, and therefore, all values are in the range of 0 to 1.

Table 2

Linguistic Variables and Membership Functions of the Fuzzy Expert System for Measuring E-Learners' Satisfaction in Mathematics

Variable	Completely Low	Very Low	Low	Medium	High	Very High	Completely High
Technical Quality System	—	[-∞ -∞ 0.1 0.25]	[0.1 0.25 0.5]	[0.25 0.5 0.75]	[0.5 0.75 1]	[0.75 1 1]	—
Educational Quality	—	[-∞ -∞ 0.1 0.25]	[0.1 0.25 0.5]	[0.25 0.5 0.75]	[0.5 0.75 1]	[0.75 1 1]	—
Info & Content Quality	—	[-∞ -∞ 0.1 0.25]	[0.1 0.25 0.5]	[0.25 0.5 0.75]	[0.5 0.75 1]	[0.75 1 1]	—
Service Quality	—	[-∞ -∞ 0.1 0.25]	[0.1 0.25 0.5]	[0.25 0.5 0.75]	[0.5 0.75 1]	[0.75 1 1]	—
Satisfaction Level	[0 0 0.1]	[0 0.1 0.3]	[0.1 0.3 0.5]	[0.3 0.5 0.75]	[0.5 0.75 0.9]	[0.75 0.9 1]	[0.9 1 1]

The mathematical definition of the membership degree for the triangular membership function is provided below in Equation (1).



$$\mathbf{A} \triangleq \mu_{\mathbf{A}}(x) = \begin{cases} \frac{x-a_1}{b_1-a_1} & \text{for } a_1 \le x \le b_1, \\ 1 & \text{for } b_1 \le x \le b_2, \\ \frac{x-a_2}{b_2-a_2} & \text{for } b_2 \le x \le a_2, \\ 0 & \text{otherwise.} \end{cases} \quad (1)$$

The knowledge base includes the fuzzy "if–then" rules and linguistic variables. After defining the initial criteria, various rules related to this satisfaction measurement system were created using the opinions of experts and specialists, and based on the weights of the criteria determined through the Fuzzy Analytic Hierarchy Process (FAHP). Considering the research context, a total of 50 important rules were developed, and some of the key rules are presented in Table 3. For example, according to Rule 2, if the system quality is very low, the instructional quality is low, the information quality is medium, and the service quality is high, then—considering the weights of system quality and instructional quality—the level of satisfaction will be very low

Table 3

Some Important Rules Generated by Experts for Designing the Fuzzy System

Row	If (System Quality)	(Instructional Quality)	(Information Quality)	(Service Quality)	Then (Satisfaction)
1	Medium	High	Very High	Medium	High
2	Very Low	Low	Medium	High	Very Low
3	Very High	High	Medium	Low	Very High
4	Very High	High	High	Very High	Completely High
5	Medium	High	Low	Medium	Medium

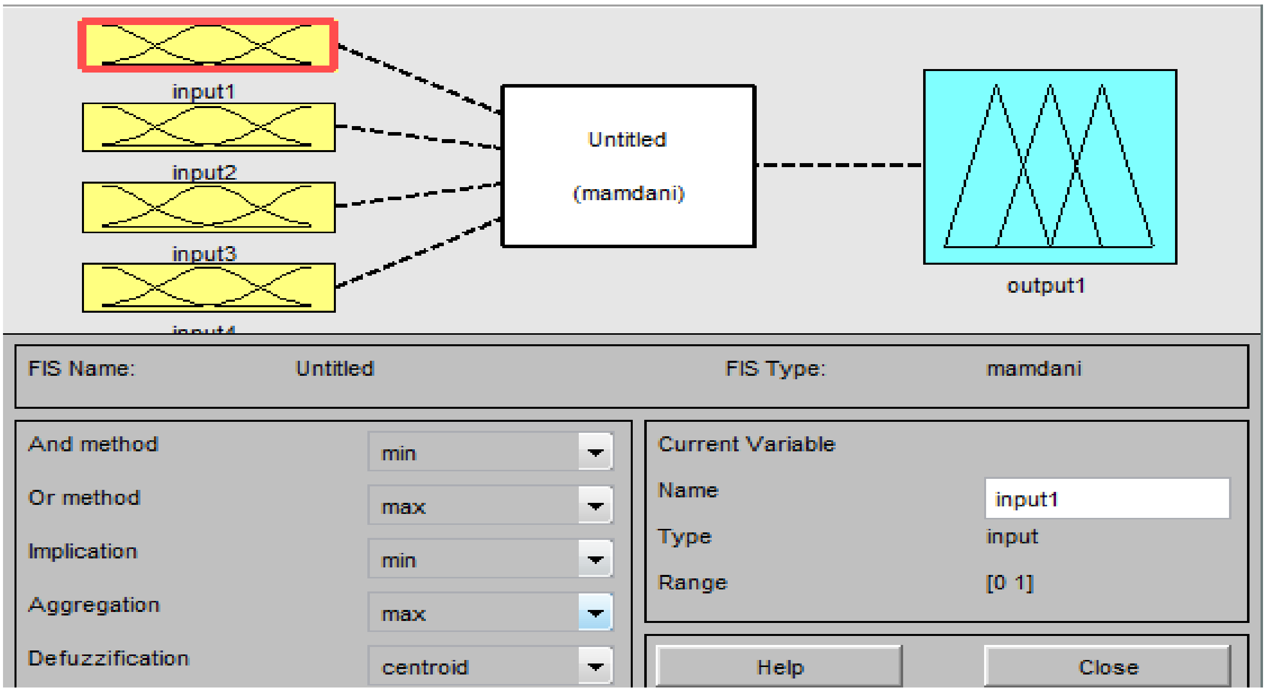
Additionally, the defuzzification of the system was performed using the centroid method. In Equation (2), Z* represents the defuzzified output value, which demonstrates the centroid calculation method:

$Z^* = (\int \mu\_i(x) * x \, dx) / (\int \mu\_i(x) \, dx)$ (2)

After determining the rules, the system was designed with four input variables — technical quality of the system and technological infrastructure, instructional quality, information and content quality, and service quality — and one output variable, satisfaction level. This system structure is illustrated in Figure 2.

Figure 2

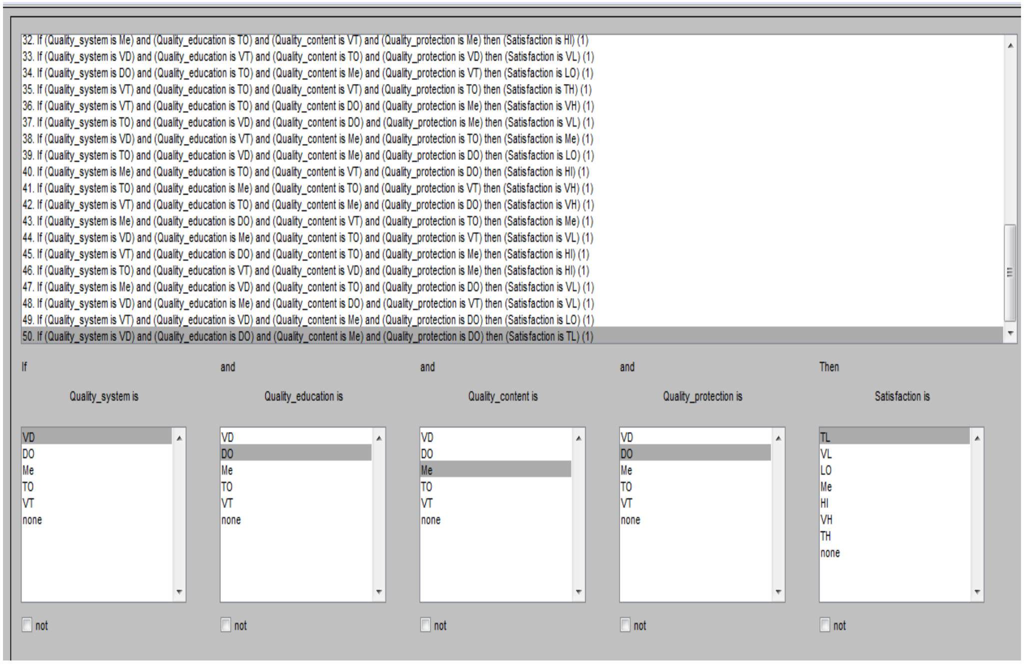
Input and Output Variables of the Satisfaction Measurement System



Furthermore, the 50 rules used in this system are depicted in Figure 3.

Figure 3

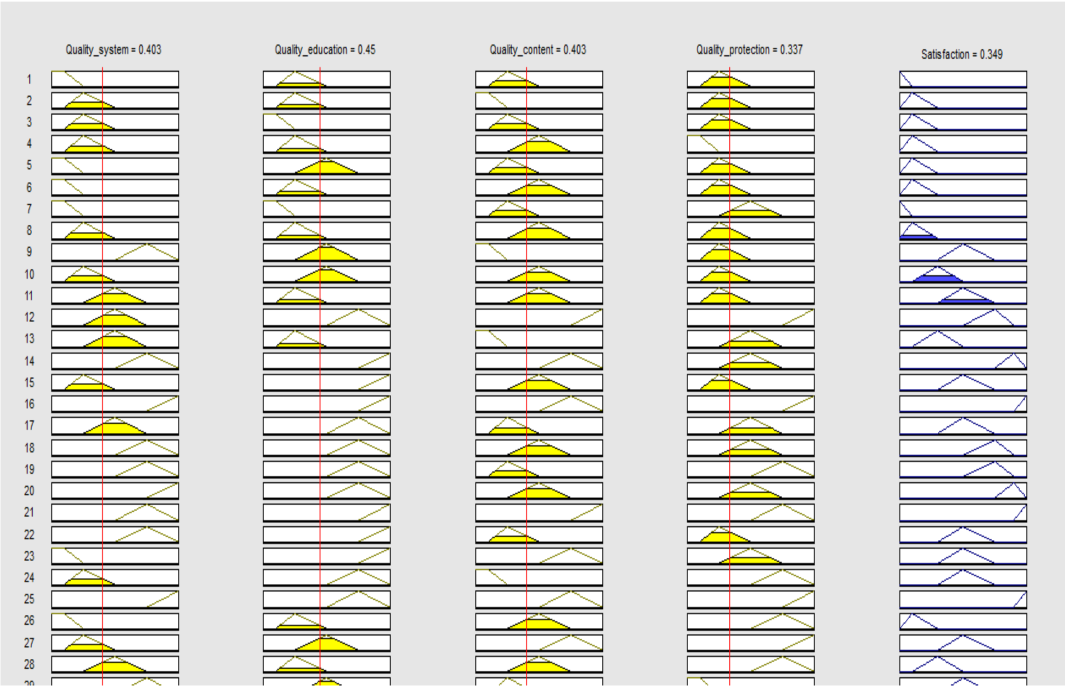
Rules Generated in the Fuzzy Satisfaction Measurement System



Considering the design of the membership functions shown in Table 2, with the given input values of technical system quality and infrastructure, instructional quality, information and content quality, and service quality, the satisfaction level of e-learners can be estimated with an error margin of less than 0.15. For example, the graphical interface with two inputs and the output of the designed fuzzy system is displayed in Figures 4 and 5, where the exact output values are shown.

Figure 4

Satisfaction Level of 0.349 for Input (0.337, 0.403, 0.450, 0.403) Based on the Generated Rules

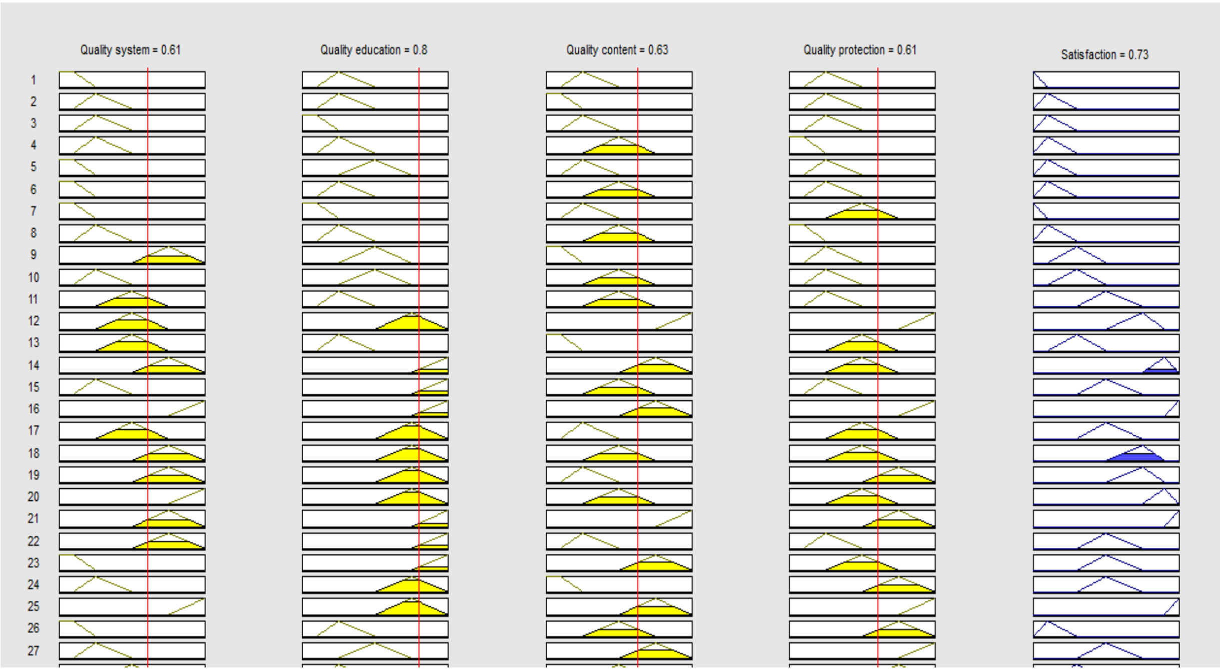


In the above system, by modifying the input components, the level of satisfaction is displayed in the corresponding output. In Figure 4, if the influential criteria in the e-learning environment are as follows — system and infrastructure quality: 0.403; instructional quality: 0.45; information and content quality: 0.403; service quality: 0.337 — then, based on the fuzzy expert system and using the centroid defuzzification method, the satisfaction level is calculated as 0.349.

Furthermore, if the influential criteria in the e-learning environment are as follows — system and infrastructure quality: 0.61; instructional quality: 0.80; information and content quality: 0.63; service quality: 0.61 — then, based on the fuzzy expert system and using the centroid defuzzification method, the satisfaction level is calculated as 0.73, as shown in Figure 5.

Figure 5

Satisfaction Level of 0.73 for Input (0.61, 0.63, 0.80, 0.61) Based on the Generated Rules



Therefore, by providing different inputs for system and infrastructure quality, instructional quality, information and content quality, and service quality, it is possible to estimate and predict the satisfaction level of e-learners with an error margin of less than 0.15. Considering the role and importance of student satisfaction in using the e-learning system, the higher the satisfaction level, the stronger the motivation and the more effective the system usage, resulting in a more efficient system.

Based on this fuzzy expert system, the satisfaction level of e-learners in the mathematics course can be determined, and actions can be taken to address deficiencies and weaknesses and strengthen the advantages of the educational system and learning environment according to their importance weight.

4. Discussion and Conclusion

The results of this study provide a systematic and evidence-based framework for assessing the satisfaction of e-learners in mathematics through the design and application of a fuzzy expert system. The findings demonstrated that learner satisfaction is strongly shaped by four interrelated dimensions: system and technological infrastructure, instructional quality, information and content quality, and service quality. The fuzzy expert system was able to model these dimensions effectively by integrating expert judgments into "if–then" rules, enabling precise estimation of satisfaction with an error margin lower than 0.15. This outcome confirms that satisfaction is not a single-dimensional construct but emerges from the interaction of technical, pedagogical, informational, and service-related factors, a notion widely acknowledged in prior e-learning studies (Mohammadi, 2015; Yakubu & Dasuki, 2018).

A key contribution of this research is the empirical confirmation of the pivotal role of system and technological infrastructure in shaping students' experience. The results showed that when the platform is user-friendly, reliable, secure, and allows flexible access, satisfaction increases significantly. These findings echo the arguments of Yakubu (Yakubu & Dasuki, 2018), who emphasized that system quality and service responsiveness are strong determinants of continued system use. They also align with Asgari's meta-synthesis (Asgari et al., 2023), which revealed usability and system performance as primary enablers of learning management system success. For mathematics learners, who frequently interact with symbolic content and problem-solving interfaces, system efficiency is particularly crucial (Jafarabadi Ashtiani & Nomanov, 2021; Pei-Chen & Hsing Kenny, 2025). A poorly performing or complex interface may increase cognitive load and discourage engagement.

The study further underlined the importance of instructional quality, particularly the system's adaptability to various learning styles, the presence of performance assessment tools, and opportunities for collaborative learning. These findings resonate with Fazeli (Fazeli et al., 2021), who argued that active and interactive teaching strategies within e-learning can directly influence motivation and satisfaction. Similarly, Cheawjindakarn (Cheawjindakarn et al., 2013) and Seraji (Seraji & Attaran, 2012) suggested that instructional quality—particularly clarity of objectives, feedback mechanisms, and learning interactivity—is a major predictor of e-learning effectiveness. In mathematics education, interactive instructional design is particularly critical because it supports conceptual understanding and problem-solving skills (Ragib, 2023). When the instructional dimension is neglected, students may perceive digital mathematics learning as passive and disengaging.

Another major result is the confirmation of the significance of information and content quality. The fuzzy system weighted attributes such as accuracy, relevance, and comprehensiveness of learning materials as central to satisfaction estimation. This result is consistent with the findings of Chen (Chen & Young Tat Yao, 2016), who showed that up-to-date and clear content strongly correlates with learner satisfaction in blended learning. Filippova (Filippova, 2015) also emphasized the role of timely and accurate content in sustaining user trust and engagement. Local research conducted at Farhangian University similarly highlighted that mathematics learners' satisfaction decreases when materials are outdated or not aligned with course objectives (Faraj Elahi et al., 2020; Gorzin Nezhad et al., 2020). The present study reinforces these conclusions by demonstrating that information quality, when integrated into an intelligent decision-making model, has measurable and predictive power.

Service quality emerged as another crucial determinant of satisfaction, particularly in providing timely technical and academic support. Learners reported greater confidence when they could access assistance quickly and when their feedback was acknowledged in system updates. These results align with Mohammadi (Mohammadi, 2015) and Maria de Lourdes (Maria de Lourdes et al., 2011), who found that technical and service support significantly predict learner motivation and retention. The integration of service responsiveness as a weighted variable in the fuzzy expert system confirms that supportive e-learning ecosystems are not merely technological but socio-technical, requiring proactive engagement from institutions.

The successful application of fuzzy logic in this research also contributes to methodological innovation in educational evaluation. Traditional surveys, while valuable, often oversimplify complex constructs such as satisfaction (Chen & Tseng, 2012; Karimzadganmoghadam et al., 2012). Fuzzy expert systems, on the other hand, can integrate subjective expert knowledge with computational reasoning to produce nuanced, actionable outputs. This approach aligns with earlier studies in educational decision-making, where fuzzy logic was employed to diagnose learning barriers and rank quality indicators (Babakordi, 2020; Dehghandar, Pabasteh, et al., 2021; Elahi et al., 2015). By applying this method specifically to mathematics e-learning in Iranian higher education, this research advances local understanding of how multi-dimensional quality constructs can be systematically evaluated and managed.

Another interesting insight from the findings is the consistency between the identified critical factors and globally recognized success frameworks. For example, the DeLone and McLean Information Systems Success Model identifies system quality, information quality, and service quality as core constructs (Yakubu & Dasuki, 2018). The present study not only validates this model but contextualizes it for mathematics e-learning by incorporating instructional quality as an explicit and high-impact dimension. This addition is supported by Pei-Chen (Pei-Chen & Hsing Kenny, 2025) and Sadeghi (Sadeghi, 2024), who argue that discipline-specific pedagogical requirements must be integrated into general success models to ensure relevance. Mathematics learning requires interactivity, problem-solving, and immediate feedback, which general frameworks often overlook.

Additionally, the fuzzy expert system developed here provides a practical solution for educational administrators. By integrating expert knowledge with data-driven rules, managers can obtain a dynamic and precise understanding of learners' satisfaction levels and the factors influencing them. This capability is crucial for institutions such as Farhangian University, where timely decisions about system upgrades, instructional interventions, and resource allocation can significantly influence students' academic success (Asgari et al., 2023; Zare et al., 2024). The ability to measure satisfaction with high accuracy and low error margins enables proactive rather than reactive management.

Finally, the study situates itself within a broader technological and educational shift toward data-driven and AI-assisted decision-making. The integration of fuzzy systems parallels advancements in artificial intelligence and machine learning that are increasingly used to predict student performance and personalize learning experiences (Reis et al., 2024). This trend signals a move away from static evaluations toward adaptive, intelligent educational management systems. By focusing on the high cognitive demands of mathematics and the unique requirements of future educators, the research offers a model adaptable to other challenging academic disciplines and institutional contexts.

While this study offers valuable insights and methodological innovation, it has several limitations that should be acknowledged. First, the research was conducted within a single institutional context—Farhangian University of Mazandaran. Although this provides depth and local relevance, it may limit the generalizability of the results to other universities with different technological infrastructures, cultural contexts, or student populations. Second, the sample of experts, although purposively selected for their experience in mathematics and educational technology, was relatively small. While expert-based fuzzy modeling thrives on quality rather than quantity, a broader and more diverse expert panel could increase the robustness of the knowledge base. Third, the evaluation relied on expert perceptions and system indicators rather than direct longitudinal tracking of learner outcomes such as course completion or grades. While satisfaction is a strong predictor of engagement and performance, integrating objective performance data would strengthen the validity of the model. Finally, the fuzzy system's design depends on the accuracy and currency of the membership functions and rules; as technology and pedagogy evolve, periodic updating of these parameters will be essential to maintain the system's relevance.

Future research could build upon this study in several ways. Expanding the sample to include multiple institutions and diverse learner groups would help test the model's adaptability across contexts and disciplines. Comparative studies between mathematics and other fields with varying cognitive demands, such as language learning or applied sciences, could refine the weight and significance of satisfaction dimensions. Integrating longitudinal data to assess how satisfaction measured by the fuzzy system predicts long-term academic performance, retention, and self-efficacy would provide deeper insight into its practical utility. Researchers might also explore hybrid intelligent systems that combine fuzzy logic with machine learning to allow the system to self-adjust and improve accuracy over time. Another promising direction is the incorporation of real-time learning analytics—such as log data, interaction patterns, and engagement metrics—to complement expert-driven indicators with live learner behavior signals. Finally, qualitative investigations into students' lived experiences could enrich the interpretation of fuzzy model outputs and guide the development of more human-centered e-learning systems.

From a practical standpoint, the findings encourage educational administrators to adopt intelligent decision-support systems to monitor and improve e-learning satisfaction continuously. Institutions should ensure that system infrastructure is stable, user-friendly, and flexible to reduce cognitive and technical barriers, especially in mathematics courses. Instructional designers should focus on creating interactive, adaptive, and problem-based content aligned with learners' needs and expectations. Regular evaluation of content accuracy and timeliness is essential to maintain learner trust and motivation. Service responsiveness—technical help, academic support, and user feedback loops—should be prioritized to create a supportive and engaging e-learning environment. Additionally, administrators should institutionalize periodic expert reviews and system updates to keep fuzzy models relevant as technology and learner needs evolve. By embedding these practices, universities can move toward data-informed and learner-centered digital education ecosystems.

Authors' Contributions

Authors contributed equally to this article.

Declaration

In order to correct and improve the academic writing of our paper, we have used the language model ChatGPT.

Transparency Statement

Data are available for research purposes upon reasonable request to the corresponding author.

Acknowledgments

We would like to express our gratitude to all individuals helped us to do the project.

Declaration of Interest

The authors report no conflict of interest.

Funding

According to the authors, this article has no financial support.

Ethics Considerations

In this research, ethical standards including obtaining informed consent, ensuring privacy and confidentiality were considered.

References

Asgari, M., Abdoli, S., Nili Ahmadabadi, M., & Fardanesh, H. (2023). Meta-Synthesis of a Comprehensive Framework of Factors Affecting the Usability of Learning Management Systems. *Technology of Education Journal*, *17*(4), 849-868. https://jte.sru.ac.ir/article_1962.html

Babakordi, F. (2020). Familiarity with Hesitant Fuzzy Sets and Their Types. *Journal of Operations Decision Making*, *4*(4), 361-353. https://civilica.com

Cheawjindakarn, B., Suwannatthachote, P., & Theeraroungchaisri, A. (2013). Critical Success Factors for Online Distance Learning in Higher Education: A Review of the Literature. *Creative Education*, *3*(8), 61. https://doi.org/10.4236/ce.2012.38B014

Chen, R., & Tseng, H. (2012). Factors That Influence Acceptance of Web-Based E-learning System for the In-Service Education of Junior High School Teachers in Taiwan. *Evaluation and Program Planning*, *35*(4), 398-406. https://doi.org/10.1016/j.evalprogplan.2011.11.007

Chen, S., & Young Tat Yao, A. (2016). An Empirical Evaluation of Critical Factors Influencing Learner Satisfaction in Blended Learning: A Pilot Study. *Universal Journal of Educational Research*, *4*(7), 1667-1671. https://doi.org/10.13189/ujer.2016.040719

Dehghandar, M., Ahmadi, G., & Aghebatbeen Monfared, H. (2021). Designing a Fuzzy Expert System for Diagnosis and Prediction of Metabolic Syndrome in Children and Adolescents. *Health Management & Information Science*, *8*(2), 79-89. https://jhmi.sums.ac.ir

Dehghandar, M., Chegini, P., & Hashemnia, S. H. (2020). Ranking of Factors Affecting Educational Quality in Payame Noor University of Karaj by AHP Method. *Journal of Research in Psychology and Education*, *4*(17), 277-290. https://www.noormags.ir

Dehghandar, M., Pabasteh, M., & Heydari, R. (2021). Diagnosis of COVID-19 Disease by the Fuzzy Expert System Designed Based on Input-Output. *Journal of Control*, *14*(5), 71-78. https://doi.org/10.52547/joc.14.5.71

Elahi, S., Rashidi, M., & Sadeghi, M. (2015). Designing a Fuzzy Expert News System for the CEO of Privacy in Electronic Government and Business Exchange. *Journal of Information Technology Management*, *7*(3), 511-530. https://journals.ut.ac.ir

Faraj Elahi, M., Pahlevani Nejad, D., Musa Kazemi, A., & Shabiri, S. M. (2020). Quality Assessment with Students' Satisfaction in E-learning, Tehran Universities. *Bi-Quarterly Journal of Educational Studies and Planning*. https://elmnet.ir/

Farhadi, R. (2015). E-learning New Paradigm in the Information Age. *Journal of Science and Technology*, *21*(1), 49-66. https://jipm.irandoc.ac.ir/article-1-116-fa.html

Fazeli, Z., Vahedi, M., & Rahimi, Z. (2021). Active Teaching in E-learning from the Perspective of Elementary School Teachers: Methods, Consequences and Challenges. *Journal of Training & Learning Researches*, *18*(1), 87-100. https://tlr.shahed.ac.ir/article_3575.html?lang=en

Filippova, T. (2015). Priority Fields of E-learning Development in Russia. *Procedia and Behavioral Sciences*, *20*(6), 348-353. https://doi.org/10.1016/j.sbspro.2015.10.063

Gorzin Nezhad, M., Darvishi Salookolaei, D., & Dehghandar, M. (2020). Evaluation and Ranking of Factors Affecting the Satisfaction of Electronic Mathematics Learners Using the Fuzzy Hierarchical Analysis Process Technique. *Quarterly Journal of Education in Basic Sciences Farhangian University*, *6*(2), 63-78. https://ensani.ir/fa/article/458154

Jafarabadi Ashtiani, M., & Nomanov, M. (2021). Mathematical e-learning based on problem solving by designing new software and investigating its effect on math performance of secondary school students. *Scientific Publications Management System*, *15*(2), 222-207.

Karimzadganmoghadam, D., Khodaparast, M., & Vahdat, D. (2012). Evaluation of Effective Factors on E-learner Satisfaction. *Iranian Journal of Information Processing & Management*, *27*(2), 461-478. https://doi.org/10.29252/acadpub.ijipm.27.2.461

Maria de Lourdes, M., Machado Virgilio Meira, B., Brites, R., Soares, J. B., & Ferreira Gouveia, O. M. R. (2011). A Look to Academic Satisfaction and Motivation in Portuguese Higher Education Institutions. *Social and Behavioral Sciences*, *29*, 1715-1724. https://doi.org/10.1016/j.sbspro.2011.11.417

Mohammadi, H. (2015). Investigating Users' Perspectives on E-learning: An Integration of TAM and IS Success Model. *Computers in human Behavior*, *45*, 359-374. https://doi.org/10.1016/j.chb.2014.07.044

Narenji Thani, F., Pourkarimi, J., & Tizhoosh Jalali, F. (2021). Identifying and Examining the E-learning Competencies for Students in Higher Education. *Journal of New Approaches in Educational Administration*, *12*(2), 1-22. http://jedu.miau.ac.ir/article_4778.html

Oulamine, A., El Gareh, F., Hattabou, & Elmenssouri, A. (2025). The evolution of e-learning and its challenges in higher

education: A theoretical review. *African Scientific Journal*, *3*(28), 174-196. http://africanscientificjournal.com
Pei-Chen, S., & Hsing Kenny, C. (2025). The design of instructional multimedia in e-learning: A media richness theory-based approach. *http://i-learn.uitm.edu.my/resources/journal/j3.pdf*. https://www.researchgate.net/publication/222414548
Poorasghar, N., Kiamanesh, A., & Sarmadi, M. R. (2015). Model for Predicting Academic Performance of Distance Education Students Based on Individual Variables, Motivational Beliefs and Self-Regulated Learning Strategies. *Quarterly Journal of Research in School and Virtual Learning*, *4*(2), 7-22. http://ensani.ir
Ragib, M. (2023). Fundamentals of e-learning in mathematics teaching: future perspectives. https://doi.org/10.51582/interconf.19-20.11.2023.015
Reis, F. J., Alaiti, R. K., Vallio, C. S., & Hespanhol, L. (2024). Artificial intelligence and machine-learning approaches in sports: Concepts, applications, challenges, and future perspectives. *Brazilian Journal of Physical Therapy*, 101083. https://doi.org/10.1016/j.bjpt.2024.101083
Sadeghi, S. H. (2024). The effect of gamified e-learning on marine ecology education: insights from Iranian maritime students. *Environmental Education Research*, 1-18. https://doi.org/10.1080/13504622.2024.2415944
Seraji, F., & Attaran, M. (2012). *E-learning: Basics, Design, Implementation and Evaluation*. Bu Ali Sina University Press. https://www.gisoom.com
Yakubu, M. N., & Dasuki, S. I. (2018). Assessing E-learning Systems Success in Nigeria: An Application of the DeLone and McLean Information Systems Success Model. *Journal of Information Technology Education: Research*, *17*, 182-202. https://doi.org/10.28945/4077
Zare, M., Nili, M. R., Ali Abadi, K., Zarei Zavarki, E., & Asgari, M. (2024). The effectiveness of a blended e-learning design model on academic performance of Farhangian University students. *Educational and Instructional Studies*(40), 126-136. https://pma.cfu.ac.ir/article_3895.html?lang=en
Zare, Z., Salehi, K., & Javadipour, M. (2023). Designing an Indicators System for Evaluation of the Performance of Teachers in E-learning Environments. *Journal of Training & Learning Researches*, *20*(1), 64-78. https://tlr.shahed.ac.ir/article_4258_05297d842c1dfebcd86ecdf020df3a1b.pdf