

# DEGREE: Development and Validation of a User Experience Model for Digital Educational Games Using Cronbach's Alpha and Fuzzy Logic

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## Abstract

*The rapid growth of digital educational games demands an evaluation model that accurately captures user experience and adopts a human-centred approach. This study introduces DEGREE (Digital Educational Game Review and Evaluation Engine), an enhanced model extending MEEGA+ by incorporating two previously underrepresented dimensions: Control and Feedback. Using a quantitative approach, questionnaires were distributed to high school students who actively use Minecraft and Duolingo, yielding 4800 responses. Reliability analysis via Cronbach's Alpha revealed that the Player Experience + Control combination achieved the highest score ( $\alpha = 0.914$ ), while the inclusion of Feedback reduced reliability ( $\alpha = 0.864$ ), leading to its exclusion in the final model. The DEGREE model consists of two core domains: Usability (Aesthetics, Learnability, Operability, Accessibility) and Player Experience (Focused Attention, Fun, Challenge, Social Interaction, Confidence, Relevance, Satisfaction, Perceived Learning, User Error Protection, Control). Evaluation scores were calculated using the Fuzzy Weighted Average (FWA) method and Mean of Maximum (MoM) defuzzification. The Control dimension emerged as the most influential (0.2735), followed by Fun (0.2664) and Satisfaction (0.2516), highlighting the significance of user agency in digital learning environments. The DEGREE model offers a statistically robust and user-oriented framework for evaluating educational games, delivering actionable insights for developers and educators to design more effective and engaging digital learning experiences. This study contributes a new validated and generalizable evaluation framework that strengthens the theoretical foundation of user experience assessment in educational game design.*

**Keywords:** Control, Digital educational games, Evaluation model, Fuzzy logic, User experience, Usability

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## 1. INTRODUCTION

Digital educational games have rapidly evolved into one of the most engaging and interactive forms of alternative learning media. In today's technology-driven learning environments, these games go far beyond functioning as mere instructional tools. They actively encourage student participation, enhance learning motivation, and enrich the way learners interact with educational content dynamically and meaningfully [1],[2].

Various elements in educational games, such as challenge, feedback, and a sense of control, have been shown to play a significant role in shaping the quality of students' learning experiences. Previous studies have found that the control dimension, in particular, positively correlates with increased user confidence, comfort, and satisfaction when interacting with digital learning platforms [3],[4]. The perceived sense of control over in-game activities can strengthen users' perceptions of learning effectiveness while also fostering more profound and more sustained engagement.

However, most widely used evaluation models for user experience in educational games, such as MEEGA+ (Model to Evaluate Educational Games based on the Learners' Experience), have yet to fully accommodate the crucial roles of the Control and Feedback dimensions within their structural

frameworks [5],[6]. This creates a gap between the actual subjective experiences of users and the formal evaluation results produced by standard instruments. In the context of digital and self-directed learning, dimensions such as Control and Feedback become even more essential—and demand accurate, intentional evaluation [7].

In this study, the reliability of various dimension combinations within the evaluation model was tested using the statistical approach of Cronbach's Alpha, which generally sets a minimum acceptable reliability threshold at  $\alpha \geq 0.70$  [8],[9]. The test results revealed that the Control dimension produced the highest Cronbach's Alpha score of 0.914 when combined with the Player Experience dimensions of MEEGA+. In contrast, the lowest reliability score, 0.864, was recorded when Control and Feedback were combined. These findings suggest that the inclusion of Control enhances the instrument's internal consistency, while the addition of Feedback appears to reduce reliability. As a result, Feedback was excluded from the final structure of the evaluation model [10].

To enrich the qualitative analysis and capture the nuances of users' subjective experiences, a fuzzy logic approach was employed, utilising the Fuzzy Weighted Average (FWA) method and a defuzzification process using the Mean of Maximum (MoM) method. The results showed that the Control dimension received the highest score at 0.2735, followed by Fun (0.2664) and Satisfaction (0.2516). These scores indicate that the sense of control is the most influential factor in shaping users' perceptions of the quality of digital educational games [11],[12].

Based on this background, the present study aims to develop a new evaluation model to enhance the MEEGA+ framework. As the foundation for model development, this research first tested three different combinations of dimensions: (1) MEEGA+ with the addition of the Control dimension, (2) MEEGA+ with the addition of the Feedback dimension, and (3) MEEGA+ with both Control and Feedback dimensions added. These combinations were then used to determine the structure of the final model.

The model was quantitatively validated using data from 4800 high school students, all active users of two popular educational games, Minecraft and Duolingo. This study is expected to significantly contribute to developing more contextually relevant evaluation instruments for digital educational game tools that are adaptive to the dynamics of interactive experiences and grounded in strong empirical evidence.

The novelty of this study lies in developing an MEEGA+-based instrument that not only expands the scope of user experience evaluation but also introduces a more refined approach to game-based instrument design. This research presents a comprehensive methodology that includes redesigning dimensions, empirical testing, and model validation based on real-world data.

The investigation was conducted systematically and in-depth to produce and validate an evaluation tool that is both theoretically robust and practically meaningful, particularly for key stakeholders such as educators, educational game developers, and researchers in learning technologies. This new model's evaluation is expected to yield relevant and actionable insights that can be applied across various academic settings, from traditional classrooms to game-based digital learning platforms.

## **2. METHOD**

This study employs a quantitative approach with an explanatory survey design to develop and validate an evaluation model for the quality of digital educational games based on user experience. The proposed model, DEGREE (Digital Education Game Review and Evaluation Engine), is an extension of the existing MEEGA+ framework, incorporating two key dimensions that have not been optimally addressed, Control and Feedback, to identify which dimension contributes most significantly to the overall evaluation.

## 2.1. Research Objects and Respondents

The study was conducted on two popular educational games, Minecraft Education Edition and Duolingo, selected to represent two distinct learning approaches: exploration-based and language-based. A total of 4,800 responses were collected through questionnaires distributed to high school students in Indonesia who had used one or both of these games in educational contexts. The sampling technique employed was purposive sampling, targeting active students as respondents. Visual representations of the Duolingo and Minecraft applications are presented in Figure 1.



Figure 1. User interfaces of Duolingo and Minecraft games

## 2.2. Research Instruments and Data Collection Procedure

The evaluation instrument was developed by adapting the MEEGA+ model and incorporating two additional dimensions. In total, there were 15 constructs, each measured by one to three items, depending on the results of the initial reliability testing. Each item used a 5-point Likert scale (1 = strongly disagree to agree 5 = strongly). The questionnaire was distributed online via Google Forms from March to April 2025. 4254 responses were collected, with 2586 respondents selecting Duolingo and 1,668 respondents selecting Minecraft. The distribution of respondent status is presented in Figure 2 [6].

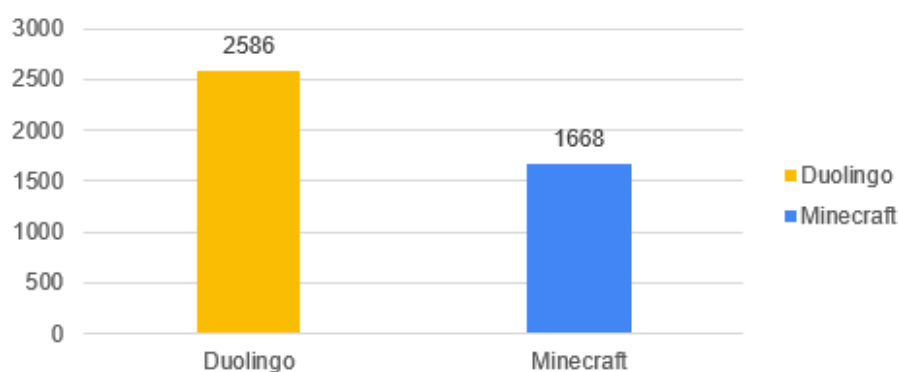


Figure 2. Distribution of Respondent Status

## 2.3. Reliability Testing: Cronbach's Alpha

Reliability testing in this study was conducted to ensure that each combination of dimensions within the evaluation model demonstrated strong internal consistency. The technique used was the calculation of Cronbach's Alpha, a widely adopted method for assessing the reliability of an instrument. Generally, an alpha value above a certain minimum threshold indicates that the instrument is dependable for measuring the intended construct. All tested combinations of dimensions were evaluated during the

analysis process, and the one with the highest reliability score was selected as the foundation for developing the new model.

## 2.4. Evaluation Score Calculation: Fuzzy Weighted Average (FWA)

The Fuzzy Weighted Average (FWA) method was employed to capture users' subjective and uncertain perceptions. Each questionnaire item was converted into a Triangular Fuzzy Number (TFN) based on the range of values from the Likert scale. The evaluation weights were determined based on the reliability and relevance of each dimension. Final scores were obtained through a defuzzification process using the Mean of Maximum (MoM) method, resulting in a final score for each dimension within the range of [0, 1].

## 2.5. The New Evaluation Model

This study proposes developing a new evaluation model to assess digital educational games' quality more comprehensively. The new model will be adapted from the existing MEEGA+ framework, but will be tested and refined based on empirical validation results, including reliability testing using Cronbach's Alpha and further analysis based on fuzzy logic. One of the main objectives of this model development is to identify the combination of evaluation factors that are most reliable and relevant.

## 2.6. Research Workflow

The research flow generally begins with developing a new evaluation model as an extension of the MEEGA+ framework, incorporating the Control and Feedback dimensions, both considered crucial yet underrepresented in previous models. The next stage involves designing and validating an evaluation instrument in the form of a questionnaire, intended to measure user perceptions across fifteen dimensions of digital educational game experience. Once the instrument was deemed valid and reliable, the questionnaire was distributed to respondents and data were collected online. A detailed illustration of the research flow is presented in Figure 3.

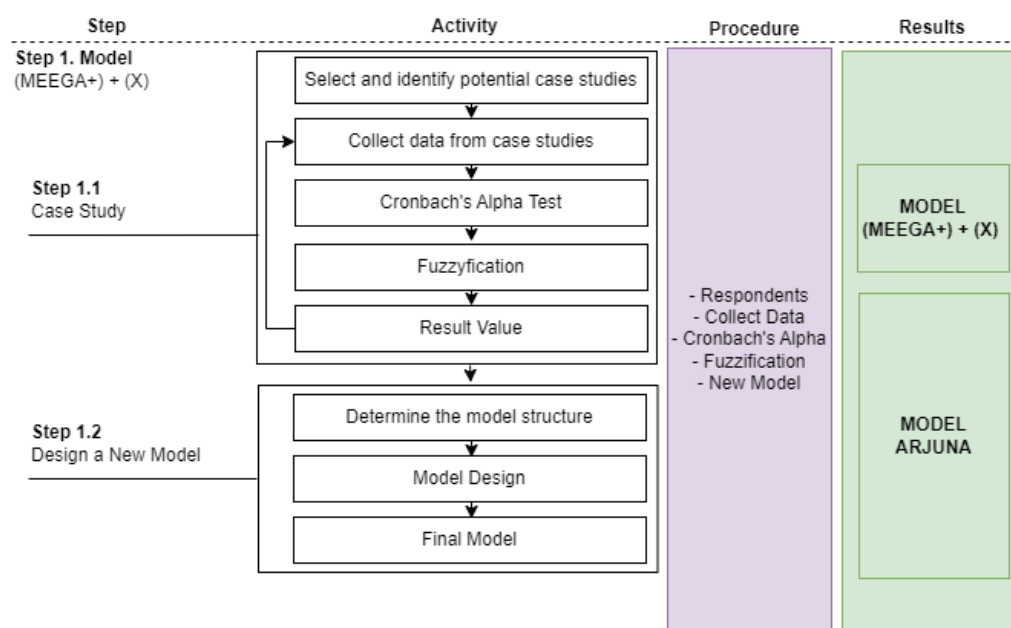


Figure 3. Research Flow

The collected data were then analysed to test the reliability of each construct using Cronbach's Alpha to ensure internal consistency among the items. The formula for calculating Cronbach's Alpha can be seen in (1).

$$\alpha = \frac{N}{N-1} \left( 1 - \frac{\sum \sigma_i^2}{\sigma_1^2} \right) \quad (1)$$

The next stage involved calculating the final quality scores of the games using the Fuzzy Weighted Average (FWA) approach combined with the Mean of Maximum (MoM) defuzzification method. This enabled a more flexible and adaptive assessment that accounts for the subjectivity of user perceptions. Finally, the results were interpreted to identify the most dominant dimensions influencing users' perceptions of digital educational game quality, providing developers with more profound and practical evaluation insights.

### 3. RESULT

#### 3.1. Reliability Test Results Using Cronbach's Alpha

Reliability testing was conducted by calculating Cronbach's Alpha for each combination of dimensions within the evaluation model. In general practice, an alpha value of  $\alpha \geq 0.70$  is considered acceptable, while values above 0.90 are categorised as excellent [9],[13]. The results of this study show that all construct combinations yielded  $\alpha \geq 0.864$ , indicating that all are reliable. The combination of Player Experience (MEEGA+) with the addition of the Control dimension recorded the highest reliability score,  $\alpha = 0.914$ , suggesting that the Control dimension strengthens the instrument's internal consistency [14]. In contrast, the lowest value was found in the combination of Player Experience + Control + Feedback, with  $\alpha = 0.864$ , indicating that adding the Feedback dimension reduced the overall reliability. These findings form the basis for the final structure of the new model, which retains the Control dimension and excludes Feedback from the evaluation components. The complete Cronbach's Alpha results are presented in Table 1.

Table 1. Cronbach's Alpha Result

Combination of evaluation factors	Cronbach's Alpha	Information
Aesthetics, Learnability, Operability, Accessibility	0.870	Usability MEEGA+
User error protection, Focused Attention, Fun, Challenge, Social Interaction, Confidence, Relevance, Satisfaction, Perceived Learning	0.901	Player Experience MEEGA+
User error protection, Focused Attention, Fun, Challenge, Social Interaction, Confidence, Relevance, Satisfaction, Perceived Learning, control	0.914	Highest value combination 1
User error protection, Focused Attention, Fun, Challenge, Social Interaction, Confidence, Relevance, Satisfaction, Perceived Learning, feedback	0.894	Highest value combination 2
User error protection, Focused Attention, Fun, Challenge, Social Interaction, Confidence, Relevance, Satisfaction, Perceived Learning, control, feedback	0.864	Highest value combination 3

The bar chart provides a clearer visualisation of the Cronbach's Alpha values calculated for various combinations of evaluation factors tested in this study. Each bar represents a version of the evaluation model based on combinations of usability and player experience dimensions, including the original MEEGA+ structure and its modified versions incorporating the Control and Feedback

dimensions. The height of each bar directly reflects the internal consistency level of each model version[15].

The increase in alpha value from 0.870 (Usability - MEEGA+) to 0.901 (Player Experience - MEEGA+) indicates that the user experience aspect generally shows stronger coherence compared to usability. Furthermore, when Control was added to the player experience structure, the alpha value increased significantly to 0.914, highlighting that this dimension enhances inter-item consistency within the measurement scale. In contrast, the inclusion of Feedback either alone or alongside Control led to lower alpha values (0.894 and 0.864, respectively), as shown by the shorter bar heights compared to previous combinations[8],[16].

Thus, the diagram reinforces the numerical results and visually communicates that incorporating Control produces the most reliable evaluation model. At the same time, adding Feedback tends to weaken measurement consistency. This visualisation supports the conceptual decision to develop a new model structure that prioritises dimensions demonstrating statistical strength and functional impact[17],[18]. The complete Cronbach's Alpha results are clearly illustrated in Figure 4.

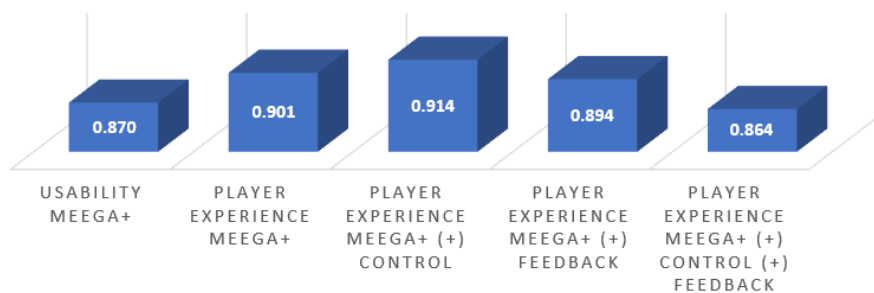


Figure 4. Bar Chart of Cronbach's Alpha Calculation Results

The heatmap analysis of correlations between evaluation dimensions reveals a clear and structured pattern of relationships. Dimensions such as Aesthetics, Learnability, Operability, and Accessibility form a distinct group, showing high positive correlations with one another, ranging from 0.61 to 0.65. These four dimensions represent the technical and ease-of-use aspects of user interaction with educational games, and are therefore consistently classified under the Usability category [19],[20],[21]. The complete heatmap analysis is visually presented in Figure 5.

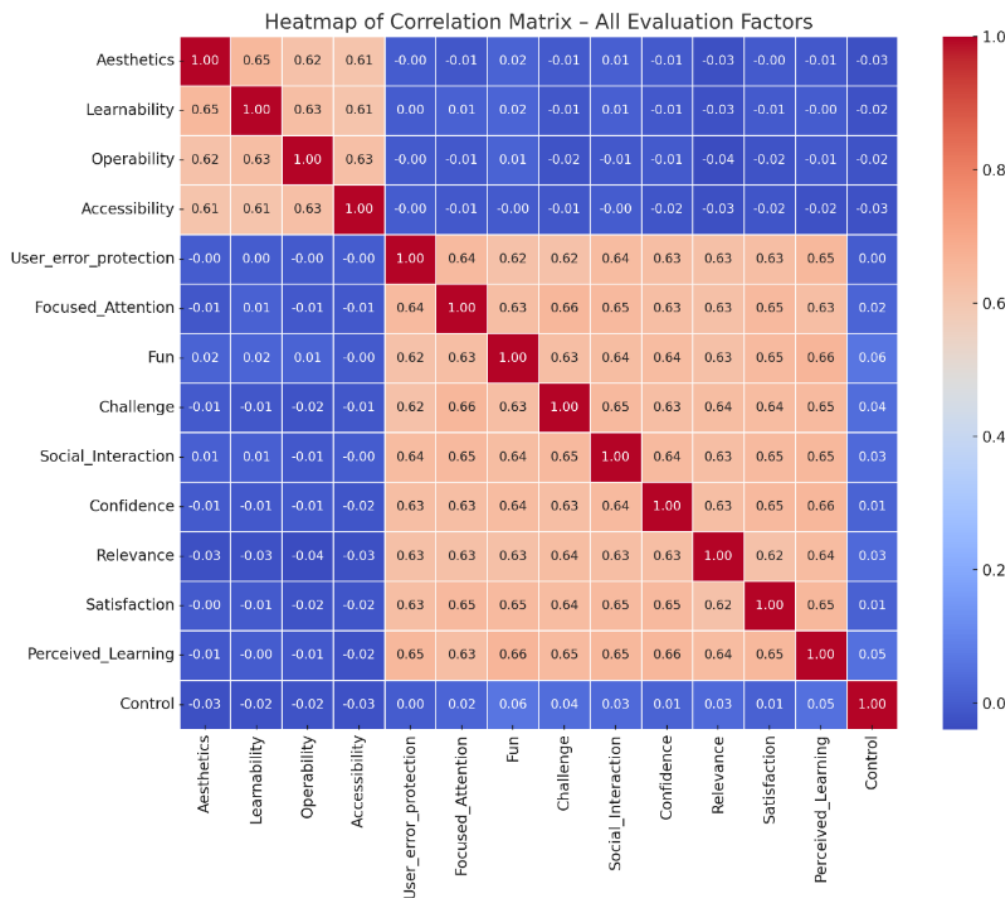
Meanwhile, dimensions such as User Error Protection, Focused Attention, Fun, Challenge, Social Interaction, Confidence, Relevance, Satisfaction, Perceived Learning, and Control also demonstrated strong internal relationships, forming a distinct group that reflects the psychological, emotional, and cognitive aspects experienced by users during gameplay[22],[23]. This group includes the control dimension, conceptually integral to player experience. It reflects the extent to which players feel a sense of agency over gameplay, interaction, and decision-making factors that ultimately influence user satisfaction and engagement [24],[25].

Based on these findings, the correlation heatmap provides a strong foundation for dividing the new evaluation model into two main pillars: Usability consisting of Aesthetics, Learnability, Operability, and Accessibility; and Player Experience comprising User Error Protection, Focused Attention, Fun, Challenge, Social Interaction, Confidence, Relevance, Satisfaction, Perceived Learning, and Control.

This structural division is further reinforced by the visual representation in the new conceptual model diagram, in which all dimensions are grouped according to their function in supporting the overall quality of digital educational games. By emphasising user agency through the Control dimension, the



new model emerges as an enhanced, more comprehensive, representative, and adaptive framework better aligned with genuine user experiences in game-based digital learning.



Matrix Figure 5. Heatmap of Correlation Matrix

### 3.2. Game Quality Score Results Using Fuzzy Weighted Average

After confirming the reliability of the combined evaluation factors through simulation, the next step was to calculate the final score for each evaluation dimension using a fuzzy logic approach. Each respondent's answer was converted into a Triangular Fuzzy Number (TFN) based on a 5-point Likert scale. The aggregation of values was carried out using the Fuzzy Weighted Average (FWA) method, with evaluation weights derived from the reliability results and the role of each construct in the user experience. The final step involved a defuzzification process using the Mean of Maximum (MoM) method to obtain representative evaluation scores [26],[27].

Fuzzy logic is particularly suitable for this study because it often handles the biases and ambiguities in digital educational game evaluations. Data collected from users tends to be subjective, involving statements like “somewhat interesting” or “very useful,” which each individual may interpret differently. By applying fuzzy logic, such subjective responses can be converted into more structured and objective quantitative data, thereby increasing the accuracy of the analysis [28],[29].

While Cronbach's Alpha was used to test the reliability of the questionnaire, this method has limitations in addressing the uncertainty inherent in respondents' answers. In contrast, fuzzy logic provides a more refined way to account for user uncertainty, making the evaluation results more representative and less dependent on traditional statistical approaches [30],[28].

Moreover, the fuzzy logic approach enhances the evaluation of various factors in the MEEGA+ model. By implementing the fuzzy model, this study was able to evaluate factors such as Aesthetics,

Fun, Challenge, and Control by incorporating more flexible linguistic scales. This allows for a more accurate capture of user perceptions than conventional methods. Thus, the fuzzy logic approach not only improves the reliability and validity of the questionnaire but also makes the evaluation process more adaptive to variations in respondent interpretation [11],[31].

In a fuzzy logic system, a membership matrix is used to determine the degree to which a respondent's answer belongs to specific categories, such as Low (L), Medium (M), or High (H). This matrix helps transform quantitative data into fuzzy values that are more flexible for analysis [32],[33],[34]. The first step involved inputting the questionnaire data into Excel. This study used data from 4,800 respondents, with responses ranging from 1 to 5 on the Likert scale. The structure of the questionnaire data table is clearly shown in Table 2.

Table 2. Structure of the Questionnaire Data Table

	A	B	C	D	E
1	Name	Aesthetics	Learnability	Operability	Accessibility
4790	Diva Salsa maharani	3	3	3	3
4791	Riska pebrianti	3	3	3	4
4792	dara syifa rahmadhani	3	3	3	3
4793	sendy mei rahmawati	3	2	3	2
4794	Muhammad Zaqi Saputra	4	3	4	4
4795	Caesya nicole piesca	3	3	3	3
4796	Rameyza elya	2	2	3	2
4797	Adin Vita Yusnia Nanda	2	2	1	2
4798	Christian Bo Constantine	3	3	3	3
4799	Viabel daffa febrian	3	3	3	3
4800	Muhammad Fikril iman	3	3	3	3
4801	Rava zaira	3	4	4	4

Next, the Fuzzy Membership Categories were determined using the Triangular Membership Function (TMF) to classify respondents' answers into three categories. The TMF method represents each Likert scale option using three values, as illustrated in Figure 6.

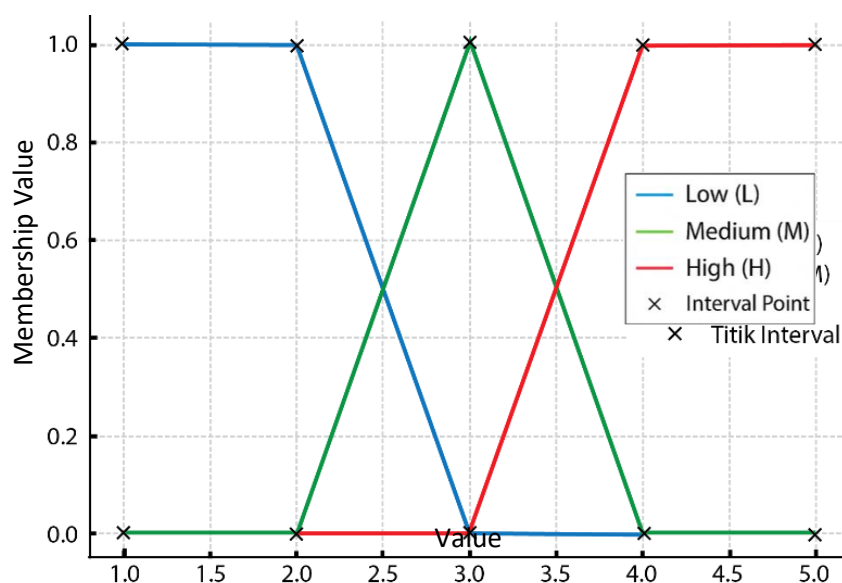


Figure 6. Triangular Membership Function (TMF)



The black cross marks indicate the interval boundaries for each category. This chart now provides a more accurate representation of fuzzy membership based on the assigned scale values. The Triangular Membership Function (TMF) graph illustrates the precise interval boundaries as follows:

- Low (L):** Covers the range [1, 2, 3] with a peak at 2. The membership function formula is presented in Equation (2).
- Medium (M):** Covers the range [2, 3, 4] with a peak at 3. The membership function formula is presented in Equation (3).
- High (H):** Covers the range [3, 4, 5] with a peak at 4. The membership function formula is presented in Equation (4).

The following membership function formulas define each of these categories:

- Low (L) Membership Function

$$\mu_L(x) = \begin{cases} 1, & \text{if } x \leq 1 \\ (3 - x)/2, & \text{if } 1 < x < 3 \\ 0, & \text{if } x \geq 3 \end{cases} \quad (2)$$

- Medium (M) Membership Function

$$\mu_M(x) = \begin{cases} 0, & \text{if } x \leq 2 \\ (x - 2)/1, & \text{if } 2 < x < 3 \\ (4 - x)/1, & \text{if } 3 < x < 4 \\ 0, & \text{if } x \geq 4 \end{cases} \quad (3)$$

- High (H) Membership Function

$$\mu_H(x) = \begin{cases} 0, & \text{if } x \leq 3 \\ (x - 3)/2, & \text{if } 3 < x < 5 \\ 1, & \text{if } x \geq 5 \end{cases} \quad (4)$$

After determining the weight of each factor through the fuzzy method, the next step in the evaluation process was to calculate the final scores using the Fuzzy Weighted Average (FWA) method. In this stage, each evaluation factor was already assigned a weight, which was used to compute the average of the user questionnaire responses.

This calculation was performed for every item representing the corresponding factor. All item-level averages were then aggregated to calculate the average scores for each factor across the Low (L), Medium (M), and High (H) fuzzy categories. This process resulted in the final average scores that reflect users' perceived quality of the digital educational game [28],[35].

The final calculation revealed that the Control dimension achieved the highest score compared to other combinations, reinforcing the finding that the Control factor significantly impacts the enhancement of the MEEGA+ model. The final fuzzy average scores are presented in Table 3.

Table 3. Fuzzy Weighted Average (FWA)

Fuzzy Weighted Average (FWA)	
Control	0.273541667
Feedback	0.272986111
Control+Feedback	0.273263889

Through the FWA approach, researchers were able to generate comprehensive evaluative scores that account for data uncertainty, thereby providing a more accurate representation of how different combinations of evaluation factors contribute to the highest overall score. This outcome is a strong foundation for constructing an improved game evaluation model, building upon the existing MEEGA+ framework [27]. A simple example of determining Fuzzy Membership Categories using the Triangular Membership Function (TMF) in Excel is presented in Table 4.

In cell E2 (Aesth L), the following Excel formula was used:  $=IF(B2 \leq 1, 1, IF(B2 \geq 3, 0, (3 - B2)/2))$ . This calculates the Aesthetics dimension's Low (L) fuzzy membership value. In cell F2 (Aesth M), the formula used was:  $=IF(B2 \leq 2, 0, IF(B2 \geq 4, 0, IF(B2 < 3, (B2 - 2)/1, (4 - B2)/1)))$ . This determines the Medium (M) fuzzy membership value. For cell G2 (Aesth H), the formula was:  $=IF(B2 \leq 3, 0, IF(B2 \geq 5, 1, (B2 - 3)/2))$ . This calculates the High (H) fuzzy membership value. These formulas produce the fuzzy membership matrix, the results of which are presented in Table 5.

Table 4. Example of Fuzzy Membership Calculation Using TMF

	A	B	C
1	<b>Responden</b>	Aesthetics	Learnability
2	Julieta	3	3
3	Dede	4	4
4	BAIQ	4	4
5	Sopiatun	3	2
6	Ajuj	2	2

Table 5. Example of Fuzzy Membership Matrix

	D	E	F	G	H	I	J
1	<b>Responden</b>	Aesth L	Aesth M	Aesth H	Learn L	Learn M	Learn H
2	Julieta	0	1	0	0	1	0
3	Dede	0	0	0.5	0	0	0.5
4	BAIQ	0	0	0.5	0	0	0.5
5	Sopiatun	0	1	0	0.5	0	0
6	Ajuj	0.5	0	0	0.5	0	0
7	<b>AVERAGE</b>	<b>0.1</b>	<b>0.4</b>	<b>0.2</b>	<b>0.2</b>	<b>0.2</b>	<b>0.2</b>

After all formulas were entered, the calculations produced a fuzzy membership matrix, in which each respondent's answer is represented by degrees of membership across the three categories. For example, if a respondent selected a score of 3 for the Aesthetics dimension, the membership value would be 0 for the Low (L) category, 1 for Medium (M), and 0 for High (H).

Subsequently, the average values for the Low (L), Medium (M), and High (H) columns of each evaluation factor were calculated using the Excel formulas:  $=AVERAGE(E2:E6)$  for Aesth L,  $=AVERAGE(F2:F6)$  for Aesth M, and  $=AVERAGE(G2:G6)$  for Aesth H. This results in average values such as: Aesth L = 0.1, Aesth M = 0.4, and Aesth H = 0.2. The final average score for each factor (e.g., Aesthetics, Learnability) was then calculated by averaging the L, M, and H values using  $=AVERAGE(E7:G7)$  for Aesthetics and  $=AVERAGE(H7:J7)$  for Learnability, resulting in values like Aesthetics = 0.233 and Learnability = 0.20.

Through this step-by-step process, the study provides a more accurate evaluation of digital educational games, reduces bias in scoring, and offers data-driven recommendations for improving game quality in the future [35].

This approach supports the assessment of game quality based on user experience and offers a solid foundation for future research in developing fuzzy-based game evaluation models.

### 3.3. Final Scores Based on Evaluation Dimensions

The evaluation began with a reliability test of the instrument using Cronbach's Alpha on various combinations of dimensions within the evaluation model. The results showed that combining Player Experience (MEEGA+) with the addition of the Control dimension yielded the highest Alpha value of 0.914, indicating excellent internal consistency. In contrast, the inclusion of Feedback, individually or alongside Control, reduced the reliability scores to 0.894 and 0.864, respectively. Based on these findings, Control was retained in developing the new model, while Feedback was excluded due to its lack of contribution to instrument reliability.

The next step involved processing 4800 respondent data entries by converting Likert scale responses (1–5) into Triangular Fuzzy Numbers (TFNs). Each value was classified into three linguistic categories: Low (L), Medium (M), and High (H). These were then averaged using the Fuzzy Weighted Average (FWA) method. The final stage used the Mean of Maximum (MoM) defuzzification to obtain the final numerical scores for each evaluation dimension.

The defuzzification results revealed that the Control dimension had the highest score of 0.2735, making it the most dominant factor influencing users' perceptions of digital educational game quality. This was followed by Fun (0.2664) and Satisfaction (0.2516), which also significantly contributed to the user experience. Other dimensions, such as Feedback (0.2398), Focused Attention (0.2281), and Challenge (0.2216), showed moderate impact, while User Error Protection (0.1792) and Accessibility (0.1678) ranked the lowest.

With consistently high reliability testing and fuzzy MoM scoring results, the Control dimension has been proven to be the most influential element in evaluating the quality of digital educational games. This finding provides a strong foundation for structuring the new model, positioning Control as an integral part of the Player Experience domain, and emphasising the need for an evaluation approach that is more adaptive and representative of actual user perceptions.

### 3.4. DEGREE Evaluation Model

The evaluation model developed in this study is named DEGREE (Digital Educational Game Review and Evaluation Engine). This model is designed to comprehensively assess the quality of digital educational games through two main domains: Player Experience and Usability. The DEGREE model is illustrated in Figure 7.

In the Player Experience domain, eleven dimensions describe the user's interaction with the game: Focused Attention, Fun, Challenge, Social Interaction, Confidence, Relevance, Satisfaction, Perceived Learning, User Error Protection, and Control. The addition of the Control dimension was based on reliability validation results, which demonstrated its significant contribution to improving the instrument's internal consistency. Meanwhile, the Usability domain consists of four core dimensions: Learnability, Operability, Aesthetics, and Accessibility. These dimensions represent the ease of use, comfort, and accessibility experienced by users when interacting with educational games.

Overall, the DEGREE model offers a structured and comprehensive evaluation framework that not only measures the technical aspects of digital games but also strongly emphasises the quality of user experience. This model is intended to serve as a practical reference for researchers, educators, and

educational game developers in evaluating and enhancing the quality of digital games in a more objective and context-sensitive manner.

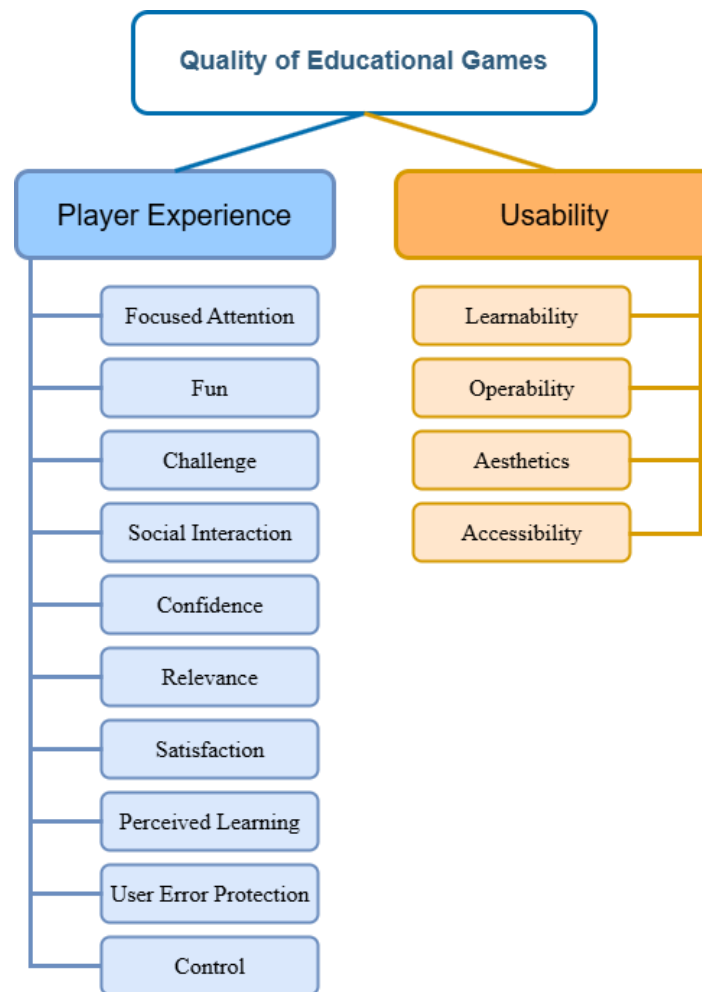


Figure 7. DEGREE Evaluation Model

## 4. DISCUSSIONS

### 4.1. The Significance of the Control Dimension in Educational Game Evaluation

The analysis revealed that the **Control** dimension is most prominent in shaping users' perceptions of digital educational game quality. This is reflected in both the highest **reliability score** ( $\alpha = 0.914$ ) and the highest fuzzy MoM evaluation score (0.2735) [31]. A sense of control over navigation, game flow, and interactive decisions was critical to creating meaningful learning experiences. Beyond its technical role, this dimension also captures **psychological aspects** such as engagement, confidence, and user autonomy during gameplay. The consistently strong contribution of the Control dimension, both statistically and perceptually, served as the foundation for the final structure of the DEGREE model, filling a gap that previous evaluation models had not addressed [11].

### 4.2. Consistency of Findings with Related Literature

The prominence of the **Control** dimension supports previous research emphasising its role in enhancing interaction quality and learning effectiveness in educational games. For example, [36]

highlighted that game control can significantly foster greater engagement and learning motivation. Similarly, [37] found that control is correlated with a sense of ownership and self-directed learning. Including this dimension in DEGREE offers a meaningful theoretical contribution, while also addressing a key limitation of the MEEGA+ model, which did not explicitly accommodate this variable [31].

#### 4.3. The Role of Other Dimensions in the User Experience

In addition to Control, several other dimensions, namely Fun (0.2664) and Satisfaction (0.2516), also recorded high scores in user perception. This indicates that emotional elements and user satisfaction remain essential components of the gameplay experience. In line with the MEEGA+ framework, these findings confirm that the evaluation structure should maintain a balanced integration of affective and cognitive dimensions [38].

Meanwhile, dimensions such as Feedback, Focused Attention, and Challenge occupied mid-level positions, indicating moderate but noteworthy contributions. On the other hand, User Error Protection (0.1792) and Accessibility (0.1678) scored the lowest, which may suggest that these features were either already adequately addressed or had limited visibility in shaping the user experience during gameplay with the selected games (Minecraft and Duolingo) [39].

#### 4.4. Contributions and Implications of the DEGREE Model

Based on consistent empirical findings, the development of the DEGREE model retained only the Control dimension from the two additional candidates tested, excluding Feedback due to its lower reliability score. The resulting model offers a new evaluation framework more responsive to user needs and integrates two main domains, Usability and Player Experience, in a structure optimised according to the actual contributions of each dimension.

With its user-centred orientation and support from quantitative validation, DEGREE not only addresses the shortcomings of previous evaluation models but also holds potential as a reference for designing and developing educational games that are more adaptive, personalised, and impactful in today's digital learning environments [28].

### 5. CONCLUSION

This study resulted in the development of a new evaluation model called DEGREE (Digital Education Game Review and Evaluation Engine), which is designed to assess the quality of digital educational games in a way that is more aligned with user experience. Through reliability testing and a fuzzy logic approach, the model was constructed as an extension of MEEGA+, with an improved evaluation structure informed by empirical findings.

One key finding is that the Control dimension consistently demonstrated the highest contribution to perceived game quality regarding reliability ( $\alpha = 0.914$ ) and final evaluation score (MoM = 0.2735). In contrast, the Feedback dimension initially considered for inclusion was found to reduce measurement consistency and was therefore excluded from the final model structure.

The evaluation process was conducted systematically, collecting data from 4800 respondents, all active users of two popular educational games. Score calculations were performed using the Fuzzy Weighted Average (FWA) method and Mean of Maximum (MoM) defuzzification, providing a comprehensive view of each dimension's contribution.

The findings confirm that user control over gameplay flow, interactions, and navigation is key to shaping meaningful learning experiences. By integrating Usability and Player Experience dimensions in a balanced structure, the DEGREE model offers an adaptive, accurate, and data-driven evaluation framework. It holds direct implications for game developers, educators, and researchers, offering a

practical reference for enhancing the quality and impact of digital educational games. Further research is recommended to test the external validity of the DEGREE model in cross-cultural contexts, different gaming platforms, and other educational levels to strengthen the model's generalizability and ensure its broader relevance.

## CONFLICT OF INTEREST

The authors declare that there is no conflict of interest regarding the publication of this paper. All stages of the research, including model development, data collection, analysis, and interpretation, were conducted independently and without any financial or non-financial influence from external parties.

## REFERENCES

- [1] Y. Li, D. Chen, and X. Deng, "The impact of digital educational games on student's motivation for learning: The mediating effect of learning engagement and the moderating effect of the digital environment," *PLoS One*, vol. 19, no. 1 January, pp. 1–21, 2024, doi: 10.1371/journal.pone.0294350.
- [2] Y. Gui, Z. Cai, Y. Yang, L. Kong, X. Fan, and R. H. Tai, "Effectiveness of digital educational game and game design in STEM learning: a meta-analytic review," *Int. J. STEM Educ.*, vol. 10, no. 1, 2023, doi: 10.1186/s40594-023-00424-9.
- [3] Q. U. Ain, M. A. Chatti, W. K. Tsoplefack, R. Alatrash, and S. Joarder, "Designing and Evaluating an Educational Recommender System with Different Levels of User Control," *CEUR Workshop Proc.*, vol. 3815, pp. 29–45, 2024.
- [4] L. Wang, A. de Vetten, W. Admiraal, and R. van der Rijst, "Relationship between perceived learner control and student engagement in various study activities in a blended course in higher education," *Educ. Inf. Technol.*, vol. 30, no. 2, pp. 2463–2484, 2024, doi: 10.1007/s10639-024-12910-w.
- [5] C. Gunduzalp, "The Effects of Digital Game-Based Learning in Technology-Oriented Course: A Case Study in the Biochemistry Department," *J. Educ. Sci. Environ. Heal.*, pp. 42–59, 2024, doi: 10.55549/jeseh.1419320.
- [6] M. P. Kurniawan, M. Suyanto, E. Utami, and Kusriani, "Educational Game Learning Quality Evaluation Tool: A Systematic Literature Review," *Proc. - Int. Conf. Informatics Comput. Sci.*, pp. 419–425, 2024, doi: 10.1109/ICICoS62600.2024.10636925.
- [7] T. Wambsganss, I. Benke, A. Maedche, K. Koedinger, and T. Käser, *Evaluating the Impact of Learner Control and Interactivity in Conversational Tutoring Systems for Persuasive Writing*, vol. 35, no. 2. Springer New York, 2024. doi: 10.1007/s40593-024-00409-x.
- [8] P. A. Edelsbrunner, B. A. Simonsmeier, and M. Schneider, *The Cronbach's Alpha of Domain-Specific Knowledge Tests Before and After Learning: A Meta-Analysis of Published Studies*, vol. 37, no. 1. Springer US, 2025. doi: 10.1007/s10648-024-09982-y.
- [9] S. Zitzmann and G. A. Orona, "Why We Might Still be Concerned About Low Cronbach's Alphas in Domain-specific Knowledge Tests," *Educ. Psychol. Rev.*, vol. 37, no. 2, 2025, doi: 10.1007/s10648-025-10015-5.
- [10] S. C. Izah, L. Sylva, and M. Hait, "Cronbach's Alpha: A Cornerstone in Ensuring Reliability and Validity in Environmental Health Assessment," *ES Energy Environ.*, vol. 23, pp. 1–14, 2024, doi: 10.30919/eseel057.
- [11] K. Chrysafiadi, M. Kamitsios, and M. Virvou, "Fuzzy-based dynamic difficulty adjustment of an educational 3D-game," *Multimed. Tools Appl.*, vol. 82, no. 18, pp. 27525–27549, 2023, doi: 10.1007/s11042-023-14515-w.
- [12] A. Primanita *et al.*, "Adaptive Hint Generation for Educational Games Using Fuzzy Logic," vol. 18, no. 1, pp. 101–110, 2025.
- [13] K. Alhumaid and M. Aassali, "Understanding the role of digital information in enhancing education in UAE: An investigation of the factors that drive continuous adoption," *Int. J. Data Netw. Sci.*, vol. 7, no. 2, pp. 513–522, 2023, doi: 10.52677/j.ijdns.2023.3.019.
- [14] C. Llorente-Cejudo, "Relationship and variation of dimensions in gamified experiences



- associated with the predictive model using GAMEX,” *J. New Approaches Educ. Res.*, vol. 13, pp. 1–12, 2024, doi: 10.1007/s44322-023-00002-5.
- [15] N. Riedel, R. Schulz, V. Kazezian, and T. Weissgerber, “Replacing bar graphs of continuous data with more informative graphics: are we making progress?,” *Clin. Sci.*, vol. 136, no. 15, pp. 1139–1156, 2022, doi: 10.1042/CS20220287.
- [16] L. Xiao, K. T. Hau, and M. D. Wang, “Revisiting the Usage of Alpha in Scale Evaluation: Effects of Scale Length and Sample Size,” *Educ. Meas. Issues Pract.*, vol. 43, no. 2, pp. 74–81, 2024, doi: 10.1111/emip.12604.
- [17] J. Talbot, V. Setlur, and A. Anand, “Four experiments on the perception of bar charts,” *IEEE Trans. Vis. Comput. Graph.*, vol. 20, no. 12, pp. 2152–2160, 2014, doi: 10.1109/TVCG.2014.2346320.
- [18] C. X. B. Yixuan Li, Emery D. Berger, Minsuk Kahng, *From Perception to Decision Assessing the Role of Chart Types Affordances in High-Level Decision Tasks*, vol. 1, no. 1. Association for Computing Machinery, 2024. [Online]. Available: <http://arxiv.org/abs/2410.04686>
- [19] S. Sohana, “Heatmap Visualization for Monitoring Health of a Large-scale Cloud System,” 2022.
- [20] J. Jylhä, “Visual Heatmaps in User Experience Design,” 2024.
- [21] F. Davila, F. Paz, and A. Moquillaza, “Usage and Application of Heatmap Visualizations on Usability User Testing: A Systematic Literature Review,” *Lect. Notes Comput. Sci. (including Subser. Lect. Notes Artif. Intell. Lect. Notes Bioinformatics)*, vol. 14032 LNCS, no. July, pp. 3–17, 2023, doi: 10.1007/978-3-031-35702-2\_1.
- [22] M. S. Alotaibi, “Game-based learning in early childhood education: a systematic review and meta-analysis,” *Front. Psychol.*, vol. 15, no. April, 2024, doi: 10.3389/fpsyg.2024.1307881.
- [23] M. Cai and C. D. Epp, “Predicting Cognitive Load Using Sensor Data in a Literacy Game,” 2024, [Online]. Available: <http://arxiv.org/abs/2405.05543>
- [24] J. Pfau and M. S. El-Nasr, “On Video Game Balancing: Joining Player- and Data-Driven Analytics,” pp. 1–25, 2023, [Online]. Available: <http://arxiv.org/abs/2308.07576>
- [25] T. Kojić, M. Vergari, S. Knuth, M. Warsinke, S. Möller, and J. N. Voigt-Antons, *Influence of Gameplay Duration, Hand Tracking, and Controller Based Control Methods on UX in VR*, vol. 1, no. 1. Association for Computing Machinery, 2024. doi: 10.1145/3652212.3652222.
- [26] D. David and A. Hussein, “A Quality Assessment Methodology for Sign Language Mobile Apps Using Fusion Of Enhanced Weighted Mobile App Rating Scale (MARS) and Content Expert Standardized Criteria,” *Appl. Data Sci. Anal.*, vol. 2023, pp. 66–77, 2023, doi: 10.58496/adsa/2023/005.
- [27] R. Nasiboglu and E. Nasibov, “Kybernetika Terms of use : EFFICIENCY ANALYSIS OF THE RULE-BASED DEFUZZIFICATION APPROACH TO FUZZY INFERENCE,” vol. 61, no. 1, pp. 109–132, 2025, doi: 10.14736/kyb-2025-1-0109.
- [28] J. Yang, “Fuzzy comprehensive evaluation system and decision support system for learning management of higher education online courses,” *Sci. Rep.*, vol. 15, no. 1, pp. 1–18, 2025, doi: 10.1038/s41598-025-01782-w.
- [29] S. Shankar, N. Padmashri, N. Shanmugapriya, S. Ramasamy, and P. S. Sruthi, “IntelliFuzz: An Advanced Fuzzy Logic Framework for Dynamic Evaluation of Student Performance in Open-Ended Learning Tasks,” *Int. J. Comput. Exp. Sci. Eng.*, vol. 11, no. 1, pp. 783–791, 2024, doi: 10.22399/ijcesen.911.
- [30] T. Kyriazos and M. Poga, “Exploring Fuzzy Logic as an Alternative Approach in Psychological Scoring Abstract :,” pp. 1–15, 2024, doi: 10.2174/0118743501337527241125044301.
- [31] P. D. Paraschos and D. E. Koulouriotis, “Fuzzy Logic-Based Dynamic Difficulty Adjustment for Adaptive Game Environments,” *Electron.*, vol. 14, no. 1, 2025, doi: 10.3390/electronics14010146.
- [32] K. Muludi, R. Setianingsih, R. Sholehurrohman, and A. Junaidi, “Exploiting nearest neighbor data and fuzzy membership function to address missing values in classification,” *PeerJ Comput. Sci.*, vol. 10, pp. 1–20, 2024, doi: 10.7717/peerj-cs.1968.
- [33] M. R. Mohd Jamil *et al.*, “Crafting a blueprint for enhancing emotional well-being in special education post-pandemic: A fuzzy Delphi approach,” *Int. J. Adv. Appl. Sci.*, vol. 11, no. 11, pp. 99–111, 2024, doi: 10.21833/ijaas.2024.11.011.

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- [34] T. S. Lee, C. H. Wang, and C. M. Yu, “Fuzzy evaluation model for enhancing E-Learning systems,” *Mathematics*, vol. 7, no. 10, 2019, doi: 10.3390/math7100918.
  - [35] P. Stiefenhofer, W. Ding, V. Zhang, and X. Liangxun, “Fuzzy evaluations mappings to model opinions: assessing academic quality in technology enhanced learning environments,” *Appl. Math. Sci.*, vol. 17, no. 4, pp. 189–204, 2023, doi: 10.12988/ams.2023.917369.
  - [36] J. Slamet and Y. Basthomi, “Assessing Gamification-Based Lms for Efl Students: a Self-Directed Learning Framework,” *Stud. Linguist. Cult. FLT*, vol. 12, no. 2, pp. 100–122, 2024, doi: 10.46687/CVHT3942.
  - [37] A. Mohebbi, “Enabling learner independence and self-regulation in language education using AI tools: a systematic review,” *Cogent Educ.*, vol. 12, no. 1, p., 2025, doi: 10.1080/2331186X.2024.2433814.
  - [38] Y. Zhu, R. Zhou, and Y. Zhang, “Designing preschool children’s educational games for enlightenment through decision analysis methods,” *Multimed. Tools Appl.*, vol. 83, no. 32, pp. 78331–78360, 2024, doi: 10.1007/s11042-024-19803-7.
  - [39] H. Hidayat, A. Komariah, B. B. Wiyono, and Y. Huda, “Impact of the Use of Fuzzy Comprehensive Evaluation Applications towards Computational Thinking Skill Students in Engineering Education,” *Int. J. Inf. Educ. Technol.*, vol. 15, no. 1, pp. 90–100, 2025, doi: 10.18178/ijiet.2025.15.1.2221.