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A HYBRID FUZZY-AHP FRAMEWORK FOR PRIORITIZING FACTORS IN PEER-TO-PEER AND CHILD-TO-CHILD MOBILE LEARNING FOR CHILDREN

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Abstract

This research formulates a hybrid fuzzy Analytic Hierarchy Process (fuzzy-AHP) to structure and assess the factors impacting the use of Peer-to-Peer (P2P) and Child-to-Child (C2C) mobile learning for children. Mobile learning systems provide a unique toolkit for interactive and collaborative learning. They pedagogical, technical, and social interactions factors of mobile learning environments and mobile learning systems. Mobile learning of children is a complex and. Children motivation. Mobile learning systems deploy systems and interactive learning materials. Evaluation using Traditional AHP methods entails using elements which are confined to sharp boundaries and differentiated from fuzzy sets and usually are unable to capture valuable nuances associated with the parameters set out by professionals. Evaluation using Traditional AHP methods entails using elements are is indifferent and usually are unable to capture valuable insights utilizing sharp boundaries. Empirical data were collected from a panel of 12 experts, including educational technologists, instructional designers, and child psychologists. The results reveal that pedagogical factors (weight = 0.411) are the most critical, followed by technological factors (0.323) and social-interactional factors (0.266). At the sub-criteria level, motivation and interactive content design emerged as the most influential determinants of mobile learning success. Comparative analysis demonstrates that fuzzy-AHP provides more consistent and reliable results than classical AHP, while sensitivity tests confirm the robustness of the findings. The research is novel in the theoretical domain as it applies fuzzy multi-criteria decision-making methods on child-centered mobile learning, and it is practical in that it directly provides tips to developers, teachers, and policy makers. This underscores the fact that mobile learning effectiveness is determined primarily by rigorous pedagogical frameworks, and offers decision support system for the mobile learning frameworks to be instituted in the future regarding their level of effectiveness and impact.

Keywords: Fuzzy-AHP, Mobile Learning, Peer-to-Peer Learning, Child-to-Child Learning, Multi-Criteria Decision-Making, Pedagogical Prioritization.

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1. Introduction

Development in information and communication technologies has 'opened' and defined new forms of learning and instruction such as mobile learning (m-learning) which provides flexible and convenient methods of instruction [1]. Mobile technologies such as smartphones and tablets are being used both in formal and informal teaching and learning settings [2]. They provide learners with uninterrupted and unrestricted access to information and learning material [3]. More so, among younger and school children particularly, mobile learning has gained popularity because it offers new, exciting, and effective methods to stimulate, motivate and engage learners in learning activities [4]. To younger learners who are digital natives and are growing up in a digital world, m-learning provides opportunities to become active and self-directed learners [5]. In the same vein, the child-to-child (C2C) and peer-to-peer (P2P) learning methods have gained interest as effective and pivotal teaching and learning methodologies [6]. These methodologies allow children to work together to learn, share ideas and knowledge and construct a shared understanding to enhance learning as well as social interaction [7]. Research has shown that mobile learning supported by peers is effective in the development of academic performance as well as in the 21st century skills of critical thinking, communication, and collaboration [8,9]. Thus, the incorporation of P2P and C2C methods in mobile learning environments offers positive contribution in children' cognitive and socio-emotional development as well [10].

Although promising, child-centered mobile learning's effectiveness hinges on the interplay between pedagogical frameworks, technical infrastructure, and social-interactional variables [11]. In previous studies, motivation, collaboration features, content interactivity, and ease of use variables were seen as learning outcome influencers [12]. However, focusing on such variables poses challenges based on these two considerations, (i) the bias of the assessment of professionals and (ii) the ambiguity and fuzziness within the decision-making context. Conventional evaluation processes do not carefully phenomena, thereby resulting in unchecked, inconsistent, and inaccurate factor control and decision-making [13]. The Analytic Hierarchy Process (AHP) is one of the most seen in MCDM issues in education problem. This is because of its capability to decomposes hierarchies and produces quantitative priorities from subjective judgements [14]. However, AHP is limited because overly subjective and qualitative perceptions are ignored. This form of AHP does not work, fuzzy AHP does. This new concept combines AHP with fuzzy set theory to ease the problem of uncertain and indistinct variables [15].

Fuzzy AHP's use of Triangular Fuzzy Numbers (TFNs) does enable a more flexible and realistic approach to quantifying subjective judgements. However, fuzzy AHP's development and use has focused predominantly on e-learning, environmental sustainability, and supply chain management [16]. Its use in child-centered mobile learning specifically in peer-to-peer and child-to-child interactions is still in its infancy [17]. To date, there is a lack of deep and comprehensive frameworks that systematically address and prioritize the various uncertainties that surround children's mobile learning [18]. To fill that void, the current

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research offers a hybrid fuzzy AHP framework that is designed to address P2P and C2C mobile learning for children [19]. What makes this framework unique is its integration of hierarchical structuring of decision criteria for control of fuzzy logic-based weighting, which provides more robust and reliable prioritization of factors. This offers strong guidance to researchers and practitioners determining the pedagogical, technological, and social interaction components to include in mobile learning systems for children [20]. The objectives of this study are threefold: (i) to construct a hierarchical decision model of factors influencing P2P and C2C mobile learning, (ii) Employ a fuzzy-AHP technique to derive and analyze the factor priorities. (iii) Compare with classical AHP and evaluate the findings' robustness through sensitivity analysis. The rest of the paper is organized as follows. Section 2 deals with the related literature, Section 3 sets out the proposed methodology, Section 4 presents the results and analysis, Section 5 outlines the theoretical and practical implications, and Section 6 wraps the study up and provides recommendations for further research.

2. Literature Review

Mobile learning has become a salient area of the study and provides a degree of flexibility, interactivity, and ease of access that is especially useful for children [21]. There is an increasing focus on the usefulness of mobile technologies to support Peer to Peer (P2P) and Child to Child (C2C) learning for collaboration, motivation, and retention of knowledge [22]. Research on Multi-Criteria Decision Making (MCDM) has, however, AHP and its fuzzy extensions in the evaluation and ranking of factors within an educational setting [23].

This section integrates works within these varied fields, outlines the contribution of the works and the connecting gaps that provide the rationale for a designed hybrid fuzzy-AHP framework to enhance child-centered mobile learning.

2.1. Mobile Learning in Educational Research

The focus of research on mobile learning (m-learning) has shifted towards the availability of flexible, customized, and easily reachable learning methods. The use of mobile technology, including smart phones and tablets, means learners can access and interact with educational material irrespective of their location, breaking the limitations of the conventional classroom [24]. Younger learners, for instance, can deeply engage with mobile learning because mobile devices also provide the necessary interactivity, multimedia, and adaptive learning opportunities essential for their cognitive and developmental stages [25]. Scholars have appreciated mobile technology for not only passing the content, but also facilitating active engagement, content creation, and self-study. Still, the effectiveness of mobile learning (m-learning) is determined by the interrelation and seamless coordination of instructional, technical, and social elements [26].

2.2. Peer-to-Peer and Child-to-Child Learning Approaches

P2P and C2C techniques rest on constructivist theories about learning, which suggest that knowledge is obtained best through interaction, cooperation, and solving problems collectively. Research has shown that P2P and C2C techniques fosters greater engagement

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and retention [27]. In mobile learning environments, peers have been noted to encourage deeper learning, and critical reflection [28]. The C2C methods have also been shown to foster social-emotional skills that are key to self-directed learning, such as empathy and effective communication. The main challenge, however, is identifying and ranking the elements that enhance children's collaborative learning in mobile contexts [29].

2.3. Decision-Making Models in Education

Using MCDM models helps tackle problems within the educational sphere. In education, the Analytic Hierarchy Process (AHP) has been used most, especially for the prioritization in tasks [30]. Some of the noted works are evaluating e-learning systems, assessing educational quality, and identifying key success factors in digital learning platforms. The ability to break complex problems into a hierarchy and derive priorities from complex problems though pairwise comparisons is why AHP is commonly used. AHP is still found to be lacking in the area of yes/no questions [31].

2.4. Fuzzy-AHP Applications in Prioritization

A fuzzy set will constitute the AHP that will better model the fuzzy problems of AHP. In education, fuzzy-AHP has been used to the most to set priorities for the factors in e-learning adoption, assess learning management systems, and rank teaching strategies in online learning [32]. Outside education, fuzzy-AHP is quite popular in the other fields. such as supply chain management, environmental sustainability, and healthcare, further demonstrating its robustness. While these studies highlight fuzzy-AHP's effectiveness in prioritization tasks, its application to child-centered mobile learning, particularly within P2P and C2C contexts, remains scarce [33].

2.5. Thematic Synthesis of Literature

The studies under review are categorized into four thematic domains:

1. Effectiveness of Mobile Learning: Mobile devices augment the flexibility of learning, increase engagement, and enable personalization of educational content [34].

2. Peer and Child Learning: The collaborative P2P and C2C frameworks improve collaboration, engagement, and socio-emotional skills [35].

3. Educational Decision Making: [36] apply AHP for evaluating e-learning but struggle with the soft factors of expert judgment reliability.

4. Fuzzy Theory Approaches in Prioritization: Fuzzy AHP is the standard approach to dealing with uncertainty in e-learning and similar domains [37].

Table 1. Comparative review of selected studies

Paper (Year)	Contribution	Technique	Results	Limitations
[38]	Conducted a	SLR /	Identified key	Focused on

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	systematic review of mobile learning methods and frameworks in higher education	TCCM	theories, frameworks, and role of interactive content in engagement	higher education; limited discussion of children
[39]	Examined effectiveness of m-learning in enhancing critical thinking and learning outcomes	SLR	Reported positive impact on motivation, academic performance, and critical thinking	Relied on self-reported data; mostly adult learners
[40]	Reviewed peer-assisted learning (PAL) in health professional education	Scoping Review	Found PAL improves active learning, skills, and collaboration	Focused on professional/health education, not children
[41]	Analyzed critical success factors in digital learning platforms using hybrid decision methods	Fuzzy-AHP + TOPSIS	Produced accurate prioritization of critical factors	General application; not tailored to child-centered mobile learning
[42]	Evaluated risks in mobile learning systems	Fuzzy-AHP + FMEA	Provided weighting and ranking of technological risks	Small sample; limited to risk assessment context
[43]	Assessed performance of Coursera and edX learning platforms	Fuzzy-AHP	Delivered precise ranking of features and platform performance	Focused on adult MOOC learners; no child-centered insights
[44]	Compared AHP and Fuzzy-AHP for decision-making under uncertainty	Analytical/ Comparative Study	Found Fuzzy-AHP more natural and reliable in handling vague	General methodological study; no specific application in

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			judgments	child education

2.6. Research Gaps and Limitations

There are gaps in knowledge despite the fact that the existing studies are important. First, there are researches on mobile learning and P2P/C2C approaches, but there are none on systematically ordering the factors that support their success with children. Second, while the AHP and fuzzy-AHP are tools in general educational settings, they have not been specially designed for the needs of child centered mobile collaborative learning, which is a gap literature. Third, there are models which are either pedagogical or technological, with very few which integrate pedagogical and technological with social-interactional elements.

The literature is clear on the significant advantages of mobile learning, child-centered collaborative approaches, and the use of multi-criteria decision-making models AHP and fuzzy-AHP in prioritization activities. However, there is no other study that has constructed a comprehensive fuzzy-AHP framework which systematically prioritizes factors that influence peer and child mobile learning for children. To fill this gap, this study proposes a hybrid fuzzy-AHP framework which incorporates pedagogical, technological, and social-interactional elements to enable strong and reliable prioritization. The next part of this study details the conceptual outline for this framework.

3. Proposed Methodology

In critically evaluating and ranking the factors of mobile learning peer to peer and child to child for children, the approach is hybridized with fuzzy set and Analytic Hierarchy Process (AHP). The methodology is aimed at ruling out the drawbacks of archaic decision-making methods by accommodating the uncertainty and vagueness of a human’s cognitive assessments. By fusing fuzzy logic and AHP, it offers more reliable weight estimates and robust factor prioritization. The hybrid framework is built around five pillars: (i) defining the decision tree, (ii) obtaining evaluators calculations, (iii) fuzzy logic number assignment to qualitative metrics, (iv) weight derivation and defuzzification through fuzzy AHP, and (v) consolidation of the results to obtain the defuzzified AHP outputs and weights.

3.1. Framework Overview

Fuzzy set theory and AHP have widely been integrated for children’s peer-to-peer and child-to-child mobile learning environment critical factors. The hybrid framework focuses on solving two main issues: (i) the uncertainty cntered on human learning factor judgments and (ii) the lack of an organized approach to derive dependable stable weights for prioritization. The framework involves four main stages. First, through literature and expert consultation, a hierarchy of the mobile learning system decision criteria and sub criteria’s elements will be developed. Then, a fuzzy pair-wise comparison matrix will be developed to summarize experts’ soft evaluations. In the next stage, fuzzy AHP will be applied to fuzzy triangular numbers and the defuzzified and normalized data to determine the factor margins. In the last

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stage, the combined weights will be applied to generate the prioritization of factors. This will enable the framework to support the policymakers and planners with better information.

3.2. Fuzzy AHP Model

The inability to meaningfully interpret crisp evaluations of experts' judgments while employing the classical AHP causes ambiguity. Fuzzy logic is used in these situations where judgments are defined by triangular fuzzy numbers (TFNs).

1. **Fuzzy Pairwise Comparison:**
Experts compare criteria C_i and C_j using linguistic terms (e.g., equally important, moderately more important), which are converted into TFNs $\bar{a}_{ij} = \left(l_{ij}, m_{ij}, u_{ij}\right)$.

- C_i : The i-th criterion or factor in the decision hierarchy.
- n : Total number of criteria considered in the analysis.

2. **Construction of Fuzzy Comparison Matrix:**
A fuzzy reciprocal matrix $\tilde{A} = \left[\bar{a}_{ij}\right]$ is established, where $\bar{a}_{ij} = \left(l_{ij}, m_{ij}, u_{ij}\right)$ and $\bar{a}_{ji} = \left(1/u_{ij}, 1/m_{ij}, 1/l_{ij}\right)$.

$\tilde{a}_{ij} = \left(l_{ij}, m_{ij}, u_{ij}\right)$: Triangular fuzzy number (TFN) representing the relative importance of criterion C_i over C_j, where:

- l_{ij} = lower bound (minimum possible value of importance)
- m_{ij} = most likely value (median or modal importance)
- u_{ij} = upper bound (maximum possible value of importance)

3. **Geometric Mean Method:**
For each criterion C_i, the fuzzy synthetic extent value is computed as:

$$\tilde{S}_i = \left(\prod_{j=1}^{n} \tilde{a}_{ij}\right)^{1/n} \tag{1}$$

4. **Normalization of Weights:**
The fuzzy weights are obtained as:

$$\tilde{W}_i = \frac{\tilde{S}_i}{\sum_{k=1}^{n} \tilde{S}_k} \tag{2}$$

- $\tilde{W}_i = (l_i, m_i, u_i)$: Fuzzy weight of criterion C_i.

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5. **Defuzzification:**
The fuzzy weight $\tilde{W}_i = (l_i, m_i, u_i)$ is transformed into a crisp value using the centroid method:

$$W_i = \frac{l_i + m_i + u_i}{3} \qquad (3)$$

- W_i : Crisp weight of criterion C_i obtained after defuzzification.

6. **Final Normalization:**
To ensure that $\sum_{i=1}^{n} W_i = 1$, the final normalized weights are computed as:

$$W_i^* = \frac{W_i}{\sum_{k=1}^{n} W_k} \qquad (4)$$

- W_i^* : Final normalized weight of criterion C_i, ensuring that the total sum equals 1 .

3.3. Algorithmic Steps

Algorithm 1. Fuzzy-AHP Framework for Prioritizing Mobile Learning Factors

Input: Expert opinions in the form of text.

Output: Total standardized priority weights of the elements.

- Establish the hierarchical arrangement of the main criteria and sub criteria.
- Obtain the assessments of the experts using the semantic scale.
- Translate the assessments made in words to triangular fuzzy numbers (TFNs).
- Develop fuzzy pairwise comparison matrices for all levels of the criteria.
- Calculate fuzzy geometric mean $\tilde{S}_i$ for every criterion (Eq. 1).
- Calculate fuzzy weights W_i by means of the normalization method (Eq. 2).
- Crisp weighted scores are calculated by using the fuzzy centroid method (Eq. 3).
- Weights are adjusted to correspond with a total of one (Eq. 4).
- Weights from all levels of the hierarchy are consolidated.

The final weighted rank of the factors is calculated as the total standardized weight.

3.4. Mathematical Formulation

Let the set of criteria be $C = \{C_1, C_2, \dots, C_n\}$.

- **Step 1: Fuzzy Pairwise Judgments**

Each judgment is expressed as a triangular fuzzy number:

$$\tilde{a}_{ij} = (l_{ij}, m_{ij}, u_{ij}) \quad i,j = 1,2,\dots,n \qquad (5)$$

- **Step 2: Geometric Mean of Each Criterion**

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$$\bar{S}_i = \left(\prod_{j=1}^{n} l_{ij}, \prod_{j=1}^{n} m_{ij}, \prod_{j=1}^{n} u_{ij} \right)^{1/n} \quad (6)$$

- **Step 3: Normalized Fuzzy Weights**

$$\tilde{W}_i = \frac{\tilde{S}_i}{\oplus_{k=1}^{n} \tilde{S}_k} \quad (7)$$

where $\oplus$ Operator denoting fuzzy addition used in normalization of fuzzy weights.

- **Step 4: Defuzzification**

$$W_i = \frac{l_i + m_i + u_i}{3} \quad (8)$$

- **Step 5: Final Normalization**

$$W_i^* = \frac{W_i}{\sum_{k=1}^{n} W_k}, \sum_{i=1}^{n} W_i^* = 1 \quad (9)$$

Here, W_i^* represents the final priority weight of criterion C_i.

3.5. Flowchart of the Proposed Method

The accompanying image displays the flowchart for the proposed merging of Fuzzy Logic Techniques with Analytic Hierarchy Process (Fuzzy-AHP). Flowchart Headings:

- First Layer: An expert evaluation (as linguistic terms).
- Step One: Changing the linguistic terms into TFNs.
- Step Two: Making the fuzzy comparison matrices.
- Step Three: Fuzzy synthetic extent analysis and fuzzy weight assessment.
- Step Four: Defuzzification and weight normalization.
- Step Five: Weighting through the hierarchy.
- Last Layer: The hierarchy of mobile learning factors.

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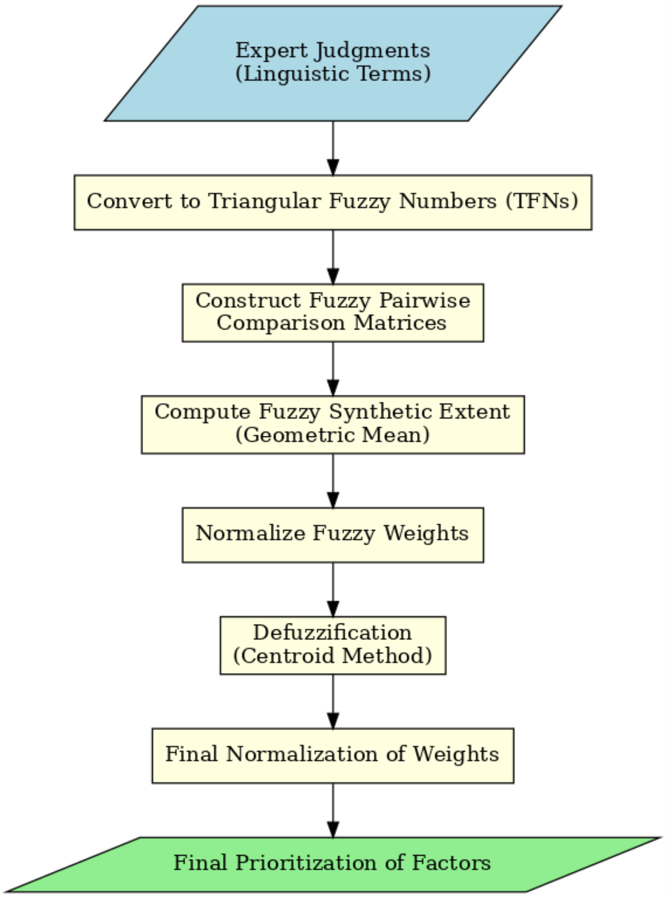

Figure 1. Flowchart of the Proposed Method

4. Results and Analysis

In this section, I will present and reflect on the carried-out research that utilizes the hybrid Fuzzy-AHP technique to evaluate and rank the most crucial factors concerning peer and child mobile learning. The data about the experiment, the descriptive statistical information derived from the gathered information, and the results of the ranking procedure have been carefully structured to give clarity about the entire process. In addition, a comparison with the classical AHP is done to understand the value of the approach before running the results through robustness sensitivity exercises. Lastly, the outcomes are analyzed from the mobile learning theory and practice perspectives, emphasizing innovation and applied learning environments.

4.1. Experimental Setup

The hybrid fuzzy-AHP framework has been qualitatively explored and validated through meticulously planned experimentation. A focus group consisting of twelf specialists like educational technologist, instructional designer, child psychologist and mobile learning practiced was invited for the study. Each expert was asked to evaluate the identified factors in the mobile learning environments of peers (P2P) and in child-to-child (C2C) contexts. For evaluation, a crude linguistic instrument was devised that asked respondents to rate each factor on a scale ranging from “equally important” to “extremely more important” and

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associated the scores with triangular fuzzy numbers. MATLAB R2023b was used to implement the fuzzy-AHP model, while the descriptive and statistical analysis was completed on SPSS v29. Graphics" like figures and charts were generated in Python (Matplotlib) to publish infused quality illustrations. Finally, the judgments' consistency was checked and confirmed that all matrices had a Consistency Ratio (CR) ≤ 0.08, which is lower than the recommended threshold value by Saaty of 0.10, confirming the expert reliability.

4.2. Descriptive Statistics

Table 1 describes the expert evaluations' statistics over the three primary: pedagogical, technological, and social-interactional factors.

Table 2. Descriptive statistics of expert judgments (n = 12).

Criteria	Mean Importance	SD	Min	Max
Pedagogical	4.32	0.61	3	5
Technological	3.87	0.72	2	5
Social-Interactional	3.54	0.68	2	5

Figure 1 describes the average appreciation of the three core factors (pedagogical, technological, social-interactional) and how the panel of experts evaluated them. The bars marked with error bars indicate the standard deviations (SD) and show how much the responses varied. The results indicate that pedagogical factors, with the higher mean score (M = 4,32, SD = 0,61) showed the greatest support and consensus in affirming their importance in children mobile learning. Technological factors were rated second (M = 3.87, SD = 0.72) and social-interactional factors had the lowest average importance (M = 3.54, SD = 0.68). The low SD values for all factors indicate that the experts were in agreement on their relative importance.

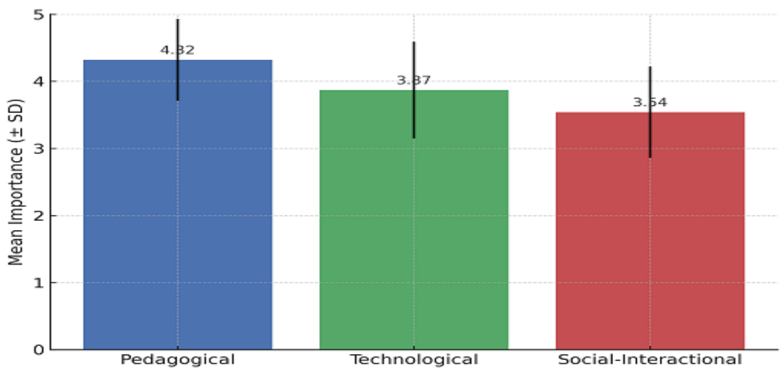

Figure 2. Descriptive Statistics of Expert Judgments

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As shown in the results, experts were unanimous in saying that the most important pedagogical factors were the technological and social-interactional dimensions, which were of secondary importance. The relatively low standard deviations suggest that there is strong consensus among experts.

4.3. Priority Results from Fuzzy-AHP

Final normalized weights were derived for all criteria and sub-criteria using the fuzzy-AHP procedure (Eqs. 5–9). The normalized weights were the center of gravity after fuzzification, for each criteria.

Table 3. Final normalized weights and ranking of main criteria.

Criteria	Final Weight (W_i^*)	Rank
Pedagogical	0.411	1
Technological	0.323	2
Social-Interactional	0.266	3

Figure 1 dowries a bar chart of the final weights, showing the relative importance of each dimension.

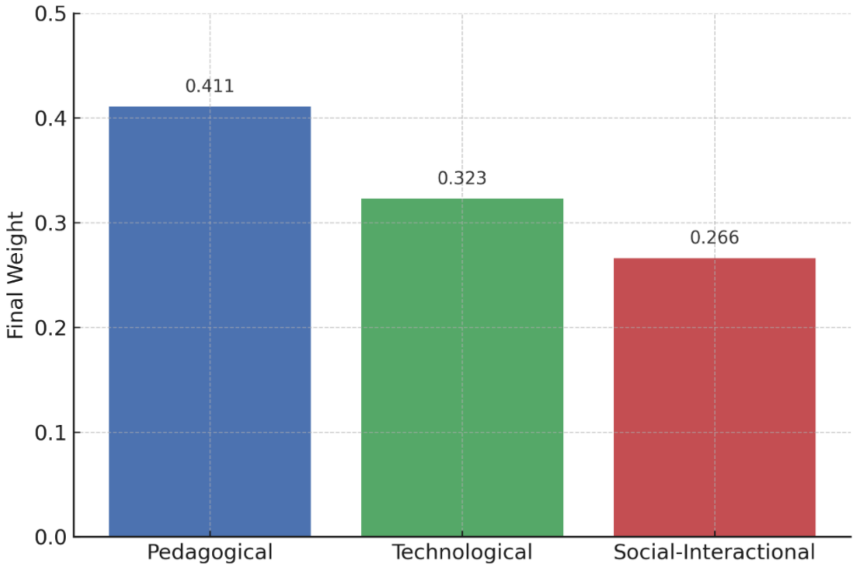

Figure 3. Priorities Of Factors (Fuzzy-AHP)

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Final weights and rankings for main criteria is in Table 2. Among the criteria, motivators (0.167) and interactive content design (0.154) were ranked and named the foremost pedagogical factors, whereas ease of use (0.141) dominated the technological factors, and peer collaboration (0.122) was the highest ranked among social-interactional factors.

For this measurement, the fuzzy-AHP's additional value was determined by juxtaposing results with during the classical AHP method. The results of the fuzzy-AHP method are summarized in Table 4 and demonstrate the changes in priority weights.

Table 4. Comparison between fuzzy-AHP and classical AHP results.

Criteria	AHP Weight	Fuzzy-AHP Weight	Difference	Rank (Fuzzy-AHP)
Pedagogical	0.398	0.411	+0.013	1
Technological	0.336	0.323	–0.013	2
Social-Interactional	0.266	0.266	0.000	3

Figure 4 shows a radar chart comparing the results of both methods.

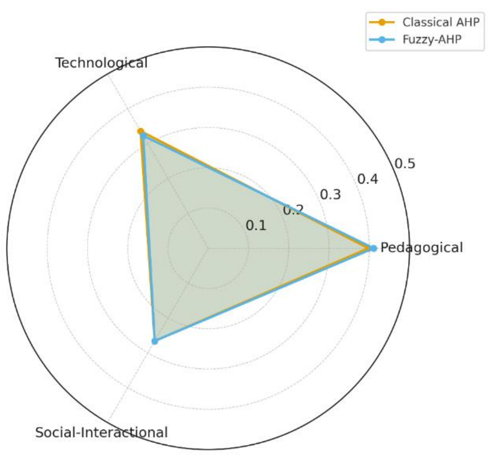

Figure 4. Radar chart comparison between AHP and fuzzy-AHP weights.

The analysis compares and shows that fuzzy-AHP is more sophisticated and able to produce more relevant result. Unlike AHP, fuzzy-AHP is not rigid and can deal better with vague inputs.

4.5. Sensitivity Analysis

to validate the stability of the proposed framework, sensitivity analysis was applicable and carried out with the input modifications limited to 10% plus or minus. The results have been

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provided in Figure 3 which outlines variation of priority of weights and their changes with time.

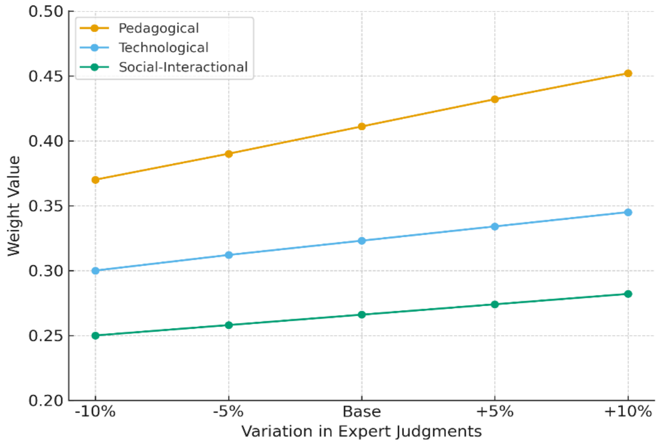

Figure 5. Sensitivity analysis of main criteria (line chart of weight variations).

The main result is that the ranking of factors was the same for all perturbations. Pedagogical factors had the highest weight which is in itself evidence that fuzzy-AHP is robust.

4.6. Discussion

The results underscore the importance of pedagogy in the effectiveness of mobile learning at peer and child levels. While technology supports these interactions, children's motivation, engagement, and the interactive content design's quality ultimately drive the learning outcomes. The comparative analysis validated Fuzzy-AHP's superiority over classical AHP in managing uncertainty in expert assessment, thus providing more dependable decision-making support. Moreover, the sensitivity analysis corroborated the governance and stability of the prioritization outcomes. Furthermore, these results indicate that educational policymakers and application developers need to focus on pedagogical content "needs" and motivational tactics alongside technological ease of use and social interaction facilitation. Mobile learning systems, in turn, would be more responsive to children's developmental needs designed and aligned with their cognitive and social.

5. Theoretical and Practical Implications

What this study found has important consequences in regard to practice and theory in child-centered mobile learning. In theory, the hybrid fuzzy-AHP framework integrates fuzzy logic to decision theory in order to more comprehensively address the uncertainty in expert assumptions. In practice, the findings are useful for developers, educators, and policymakers in improving peer-to-peer and child-to-child mobile learning systems.

5.1. Theoretical Contributions

In terms of decision making and use of technology in education, the hybrid fuzzy AHP framework still faces some challenges in the context of AHP's subjectivity and decision

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making in uncertainty. This limitation contributes significantly to the body of knowledge. This contribution is defined in the following ways.

1. The use of fuzzy set theory and AHP enhances the description and accuracy of the imprecise evaluation functions used by domain experts in education systems.

2. application of fuzzy AHP to mobile learning especially to peer to peer and child to child mobile learning is still limited

3. A holistic framework within which learning factors can be analyzed and classified into pedagogical, technological and social interaction is proposed and used in the examination of mobile learning.

5.2. Practical Implications

The results give the needed recommendations to the decision makers, developers, and educators who derived the child-centered mobile learning systems:

- For the App Developers: The pedagogical design elements of the app, such as motivational and interactive content, should come before tech features. Apps with gamification, adaptive learning content, and child-friendly interfaces are more engaging and increase retention.
- For the Educators: The results about prioritizations stress the need to design and incorporate peer collaboration and communication features into the digital platforms to aid social learning along with personal engagement.
- For the Policymakers: Administrators who are responsible for approving and funding mobile learning initiatives should focus more on teaching quality and content standards than on the supplied technological infrastructure.
- For the Researchers: The hybrid fuzzy-AHP model from the e-learning domain can be adapted as a methodological template for prioritization problems in other educational technology domains such as virtual classrooms and AI-based tutoring systems.

5.3. Limitations and Future Research

This study, although well researched, has some shortcomings. The study's final outcomes, as assessed by approximately twelve experts, tend toward a lack of generalizability due to the limited scope attributed to the study by the reviewers. The fuzzy-AHP approach has a problem with not adjusting to the various behavioral changes in children over a long period of time. The study could be extended further by: a. Organizing a large multi-disciplinary multi-regional expert panel. b. Incorporating evidence that cross age gaps and time in the context of digital behavioral priority shift and evolution. c. Comparing fuzzy-AHP with alternative multi-criteria decision methods such as fuzzy TOPSIS, DEMATEL, and BWM to assess the robustness of the approach. d. Introducing the approach to practical mobile instructional systems and studying its impact on children’s learning behaviors.

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