Modeling Educational Strategies in Augmented Reality Learning Using Fuzzy Weights

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***Abstract*—This paper shows the development and application of a fuzzy weight model methodology for the optimization of educational environments in augmented reality. A technology-based learning process in an augmented reality learning environment, notoriously able to improve spatial abilities and increase user engagement with the material learned as well as knowledge retention, has revolutionary potential in education. However, its effectiveness varies greatly. In this, we collaborated with 13 experts in augmented reality and education to deeply evaluate the following six key in-depth strategies: interactive feedback, gamified leaderboards, challenges, personalized learning path, AR-based simulations, and badges. Thus, strategies were rated upon the impact on the learners' outcome, and the ratings were agreed upon as a fuzzy set, because it is a subjective matter of evaluation. Normalization was done to get a balanced measurement that gave weights on which strategies are to be given higher priority. Such a model has been developed and implemented in a case study of AR-based spatial ability training application, focusing on AR-based simulations supplemented with interactive feedback. Pre- and post-tests among 30 respondents have shown significant improvements in the experimental group using the AR application over the control group using traditional means of spatial ability training. The results strongly support the potential of the model for later implementation in AR educational applications that focus on individual specifics and effective learning.**

Keywords—Augmented reality; educational technology; fuzzy weights; spatial ability training; educational strategies

I. INTRODUCTION

Education is one of the new roads, by which the technology of augmented reality is enriched or, on the contrary, offers unprecedented possibilities to involve the students in an immersive, interactive learning environment. This is the technology that superimposes digital information on top of the real world, making it possible for the learners to interact with virtual objects in the physical space [1], [2], [3], [4], [5], [6], [7]. Augmented reality has been shown to improve such educational outcomes as spatial ability, user engagement, and knowledge retention.[8], [9], [10], [11], [12], [13], [14]. Understanding and optimization of AR techniques in educational settings rise to be a highly important topic with the changing educational paradigms toward more technologically oriented approaches.

Further, there are many studies proving that AR can be very successful for education [15], [16], [17], [18], [19], [20]. Recently, AR was used in training spatial abilities, which is a very important factor in most work spheres, such as engineering, architecture, or medicine. It is in this sense that it has been shown that AR can present dynamic visualizations that enhance the understanding of learners concerning complex spatial relationships, which are quite hard to show by traditional methods. Besides, the interactive nature of AR stimulates active participation, which is one of the prerequisites for deeper cognitive processing and long-term memory.

Still, not all AR methods of education have to come up to be equally successful. Quite on the contrary, different educational strategies used within AR learning environments may enormously vary, insofar, that is, as these strategies are differentially well-aligned with the needs of the learner and the educational goals [21], [22], [23], [24], [25], [26], [27], [28]. This is the reason why a systematic approach will evaluate and optimize strategies within educational AR, which will ensure that AR applications are providing personally appropriate and effective learning experiences.

This paper posits the development of a fuzzy weight-based model for educational strategies within learning environments targeted at AR-based learning. Fuzzy logic is a multi-valued concept of logic consisting of fuzzy set theory, which allows us to reason from information that is imprecise or somehow variable. It is very useful within educational setups, where qualitative and subjective assessments are high. The concept of fuzzy weights may allow creating a model that will depict the relative importance of the different skills, based on expert opinions, thereby creating a fine-grained framework that can account for the complexities and variabilities exhibited within the educational practices.

The latter capitalizes on insights borrowed from experts working in the field of augmented reality and related educational technology. These experts evaluate different educational strategies, such as interactive feedback, gamified elements, personalized learning paths, and AR-based simulations. From the evaluation of the experts, one can now derive average scores on each strategy and change these scores to fuzzy sets before normalizing them to have a balanced evaluation. This will give weights to different strategies within the fuzzy set, according to the perceived strength of the impact that the strategy might have in enhancing learning experiences.

This paper addresses the design and application of a fuzzy weight-based model for educational strategy optimization within AR learning environments. With the expertise of the professionals in AR technology and educational methodologies, impact assessment of diverse educational strategies such as interactive feedback, gamified elements, personalized learning paths, and AR-based simulations will be carried out on learner outcomes. This entails receiving expert judgments, fuzzifying these judgments, and then normalizing the results to find weights to be attached to each strategy.

This paper, therefore, is meant to give subtle guidelines to drive the implementation of AR applications in education so that these applications are fine-tuned to meet the learner's needs and the result of the achievement of learner education goals. This paper, therefore, gives not only a description of the methodology in the fuzzy weight-based model but also illustrates it with a case study in the area of AR spatial ability training. In this line, it is evident that the model holds the potential to increase learner engagement, while at the same time enhancing the learning, therefore providing crucial contributions to the educational technology field and the general goal of improving educational outcomes through modern AR solutions.

The remainder of this paper is organized as follows: Section 2 details the development of the fuzzy weight-based model for educational strategies in AR learning environments. Section 3 presents a case study on the application of the model in an AR-based spatial ability training context. Section 4 discusses the evaluation results, highlighting the effectiveness of the proposed model and the AR application. Finally, Section 5 addresses the limitations of the study and suggests directions for future research to further refine and expand the application of fuzzy weight-based models in educational technology.

II. DEVELOPING THE FUZZY-BASED MODEL FOR EDUCATIONAL STRATEGIES IN AR LEARNING ENVIRONMENTS

We first developed the fuzzy weight-based model through expert opinions about the effectiveness of each educational strategy in improving learners' logical reasoning, engagement, and knowledge retention in AR-based learning. It is done through an expert panel with immense experience and knowledge in AR technology and educational methodologies. In this research, 13 experienced experts were involved. They all worked as educators or instructional designers or AR developers and, therefore, had extensive experience, involved from educators and had a broad background of the effectiveness of each of the educational strategies. Experts were asked to rate six particular educational strategies: interactive feedback, gamified leaderboards, challenges, personalized learning paths, AR-based simulations, and integration of badges, but the intent of those is not stated.

The selection of these precise strategies was based on their prevalence within AR-enhanced educational applications and on their ability to create the highest impact on the outcomes associated with augmented learning. The experts were asked to rate these strategies on an impact scale from 1 to 10, where 1 assumed minimal impact and 10 assumed maximal impact on objectives in terms of enhancing logical thinking, engaging students in the learning process, and boosting learners' knowledge. To get these estimations of the impact, we had developed a survey containing a detailed description of each of the strategies, both quantitative and qualitative questions. The quantitative section involved a rating scale with six items from one to six—one item for each of the strategies—whereas the qualitative section invited the expert to give more information and to provide, in addition, an explanation justifying their assessment.

The process of fuzzy logic allows us to address the uncertainty and subjectivity of human perception somehow by taking the levels of the impact and dividing them into the following: low, medium, and high. This translation is included in order to consider inherent variability in human judgment and to allow the model to subtly infer in regard to the potential effectiveness of a strategy. Based on the trapezoidal membership functions in Table I, the model incorporates fuzzy logic in order to deal appropriately with imprecisions and uncertainties inherently linked to human cognitive assessment, as illustrated in Fig. 1.

TABLE I. MEMBERSHIP FUNCTIONS

Impact Level Membership Function
$\mu_{LOW}(x) = \begin{cases} 1\,; & x \leq 2 \\ 1 - \dfrac{x-2}{2}\,; & 2 < x \leq 4 \\ 0\,; & x > 4 \end{cases}$
$\mu_{MEDIUM}(x) = \begin{cases} \dfrac{x-3}{2}\,; & 3 < x \leq 5 \\ 1\,; & 5 < x \leq 7 \\ 1 - \dfrac{x-7}{2}\,; & 7 < x \leq 9 \\ 0\,; & x \leq 3 \text{ or } x > 9 \end{cases}$
$\mu_{HIGH}(x) = \begin{cases} \dfrac{x-6}{2}\,; & 6 < x \leq 8 \\ 1\,; & x > 8 \\ 0\,; & x \leq 6 \end{cases}$

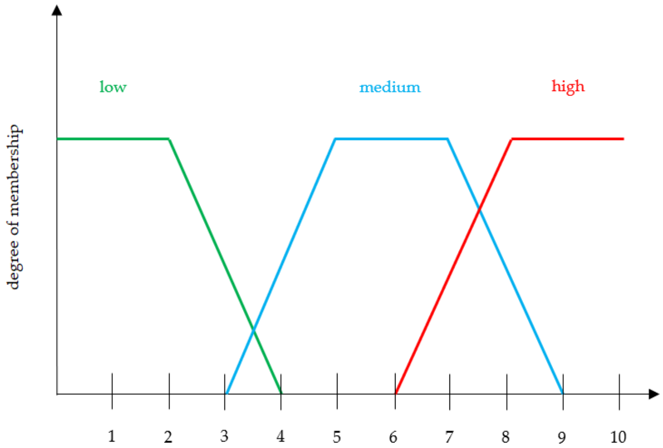

Fig. 1. Fuzzy weights schemes.

First, we calculated the average score for each educational strategy based on the ratings provided by all experts (Table II). These average scores were to be transferred into fuzzy sets. For instance, scores between 1 and 4 were categorized as "low impact," scores between 5 and 7 as "medium impact," and scores between 8 and 10 as "high impact". The boundary conditions of the membership functions have been concretized in several steps in an iterative process and in cooperation with the experts in a way so that the pairwise differences of the perceived impact levels were realized.

TABLE II. FUZZY LOGIC CONVERSION

Educational Strategy	Average Score	Fuzzy Set Category
Interactive Feedback	8.46	High
Gamified Leaderboards	6.54	Medium
Challenges	7.77	High
Personalized Learning Paths	8.38	High
AR-Based Simulations	8.77	High
Badges	3.54	Low

For each strategy, a number of fuzzy scores were given in a fuzzy set, each indicating a different level of impact. For instance, a strategy scored with a mean score of 6.5 might have a medium impact with a high degree of membership in the "medium impact" and hence need a lower degree of membership in the "high impact" set. It is in such a sense that the gradation in experts' opinions can be taken, captured, and attached to the model in representing the effectiveness of the strategies in a more concrete manner.

The sum across elements was normalized to 1 so that total weight across elements equals 1. In doing so, we divided the mean score of each element by the sum of all mean scores. Normalization scales the value of scores onto a common scale, which can be fairly compared and added up into the model. We then calculated the sum of the normalized fuzzy scores of all strategies. Then we converted the fuzzy scores into weights associated with the relative importance of the strategies. These weights provide expert opinion consensus as to the importance of an educational strategy in adding value to the AR-based learning experience. The derived weights are presented in Table III.

TABLE III. FINAL WEIGHTS FOR EDUCATIONAL STRATEGIES

Educational Strategy	Weight
Interactive Feedback	0.206
Gamified Leaderboards	0.159
Challenges	0.189
Personalized Learning Paths	0.204
AR-Based Simulations	0.203
Badges	0.086

These weights give a priority list of strategies according to the level of effectiveness, therefore, weights toward the higher range should be put into AR educational applications with the most import to be able to affect the most impact on learners.

III. Application of the Fuzzy Weight-Based Model in AR Spatial Ability Training

This is further implemented using a case study in this section of the proposed fuzzy weight-based model: A case study has been implemented in an AR-based learning application. In our case, a fuzzy weight-based model was implemented in an AR application targeted at spatial skill development [29], [30].

It is indeed a vital skill in the field of engineering, architecture, and medicine. The concepts and operations of three-dimensional objects must be well understood [31]. The spatial ability was not possible to teach using traditional methods since the episode of spatial skills does not offer the interactive and immersive experience necessary for deep learning. AR's unique ability to overlay digital content onto the real world is because it can generate effective and realistic training environments [32].

The weights that were used from the proposed model were utilized in an attempt to incorporate the most effective strategies for education in the AR-based simulations, personalized learning path, and interactive feedback in the AR application, since these possessed the highest weights in our expert evaluations. The present AR application, in this regard, attempted to highlight the most effective educational strategies to maximize learner outcomes.

The AR spatial ability training application was constructed with two significant components, AR-based simulations and interactive feedback. Both of them were interdependent on the learner's path. The AR-based simulations engaged learners in a realistic 3D environment where they learned spatial tasks. Some of the exercises mentioned in the following list are the mental rotation, the spatial visualization, and the spatial orientation. It was possible to rotate the viewed object, view the object from a different angle, and try to assemble parts of a model that had been disassembled. They constituted a challenge in the use of a challenging yet achievable progressive learning curve.

The AR-based experiential learning environments allowed trainees to manipulate the virtual elements as they would do in the real world, thereby improving the realism of the simulations. This practice could facilitate more competent development of spatial skills in learners than is possible by traditional methods.

Interactive feedback was part of the learning process. The feedback design of the system is planned so that it is immediate and context-embedded to respond to the learner's action. For example, during the construction of a virtual model, if a learner erred, the system would highlight the error and give indications on how to rectify it. Immediate feedback makes the learners realize their errors and learn from them immediately.

The system was also adaptive, meaning it adjusted in response to the learner's performance. For those who were lackluster in some aspects, the system offered more detailed advice and practice opportunities, and for those adept at the tasks, the system would increase the level of difficulty to keep them motivated and engaged. It is an adaptive approach to ensure that each learner gets the kind of support that best works for his or her needs and progress at a certain point.

IV. Evaluation Results

An experimental study was carried out among 60 participants to determine the efficacy of an AR spatial ability training application. Participants were placed into the experimental group (group A), which was taught using the AR application, and the control group (group B), which was trained using the traditional training method. Pre-tests were first run on all these participants to determine their baseline spatial ability. The experiment ran over a period of four weeks, and that included the use of the AR application by the experimental group, and the same group under traditional teaching methods, so that in the measurement of any improvements to spatial ability, both groups now took post-tests.

In estimation, it will compare improvements in spatial abilities in both groups, in which the AR-based educational strategy is given priority, using the fuzzy weight-based model. A pre-test drawing on the crucial basic spatial abilities was carried out, and all the students had taken the test prior to the training. Tasks were selected from the mental rotation, spatial visualization, and spatial orientation, which are regarded as the most important in spatial ability. The scores of this pre-test acted as the baseline for measurement of improvement.

After a training period of four weeks, during which the experimental group used the AR spatial ability training application and the control group used traditional methods, both groups completed a post-test identical to the pre-test. The difference in pre-test and post-test scores was used to assess the effectiveness of the training methods. Table IV presents the results of the *t*-test evaluation.

TABLE IV. T-TEST RESULTS OF PRE-TEST AND POST-TEST

	Group A	Group B
Pre-test Mean	2.833	2.467
Post-test mean	4.733	3.800
Difference	1.900	1.333
Standard Deviation	0.648	0.900
Pearson Correlation	0.079	-0.589
t Stat	-13.714	-4.492
p-Value	<0.001	<0.001

To analyze the results, we used hypothetical pre-test and post-test scores. The pre-test and post-test scores (on a scale of 1 to 5) for the experimental and control groups are presented in Tables V and VI:

TABLE V. T-TEST: PAIRED TWO SAMPLES FOR MEANS OF GROUP A

	Pre-test	Post-test
Mean	2.833	4.733
Variance	0.420	0.202
Observations	30	30
Pearson Correlation	0.079	
Hypothesized Mean Difference	0	
df	29	
t Stat	-13.714	
P (T < = t) one-tail	<0.001	
t Critical one-tail	1.699	
P (T < = t) two-tail	<0.001	
t Critical two-tail	2.045	

The analysis of the results of group A (Table from the pre-test (M = 2.833, SD =0.648) and post-test (M = 4.733, SD = 0.648) indicate that the use of the proposed personalized AR application resulted in an improvement in students' spatial skills, $t(29) = -13.714$, $p < 0.05$. Furthermore, the Pearson correlation value of r = 0.079 suggests a positive correlation between the pre-test and the post-test scores (Evans, 1996).

TABLE VI. T-TEST: PAIRED TWO SAMPLES FOR MEANS OF GROUP B

	Pre-test	Post-test
Mean	2.467	3.800
Variance	0.809	0.855
Observations	30	30
Pearson Correlation	-0.589	
Hypothesized Mean Difference	0	
df	29	
t Stat	-4.492	
P (T < = t) one-tail	<0.001	
t Critical one-tail	1.699	
P (T < = t) two-tail	<0.001	
t Critical two-tail	2.045	

The analysis of the results of group B (Table V) from the pre-test (M = 2.467, SD = 0.900) and post-test (M = 3.800, SD = 0.900) indicate that the traditional educational method also resulted in an improvement in students' spatial skills, $t(29) = -4.492$, $p < 0.05$. The correlation between the scores of group B is -0.589, suggesting another acceptable correlation.

The quantitative results showed a significant improvement in the spatial abilities of the experimental group compared to the control group. Participants in the experimental group demonstrated higher gains in tasks involving mental rotation, spatial visualization, and spatial orientation. They also reported higher levels of engagement and satisfaction with the training process

Besides these quantitative evaluations, data involving participant engagement and satisfaction were captured in the questionnaires. Participants from the experimental group exhibit higher rates of engagement and enjoyment over the entire process of training. They have perceived this to be very motivational, with interactive feedback and realistic simulation through the AR application in understanding spatial concepts. A participant, in this regard, commented, "Concretely, the 3D object manipulation makes the learning at hand much more concrete and intuitive". The immediate context-sensitive feedback makes the detection and correction of errors fast, and in turn, the learning process more effective.

The fuzzy weight-based model, therefore, identifies the educational strategies to be effective. The huge weight associated with AR-based simulations and the interactive feedback were justified by the resultant scores received from the experimental group. It was these strategies that were accountable to provide a wonderful learning environment, which is no doubt immersive and supportive and largely contributes to increasing the spatial abilities of the participants.

AR-based simulations thus enable the practice of spatial tasks within a controlled, yet realistic setting. The quality of the AR-based simulation qualitatively enhances the learning experience of the participant in grasping and retaining the understanding of spatial concepts. The activities of receiving timely and adaptive guidance with the aid of interactive feedback enable the learners to alter their behavior to enhance performance with constructive and immediate responses.

This outcome in the evaluation of the application AR spatial ability training clearly depicts the vast benefit of integrating the AR technology and the fuzzy weight-based educational strategies in improving spatial abilities. Of major importance is how the experimental group has indeed achieved higher improvement scores than that obtained by the control group, and this only goes on to show the benefit of integrating the AR-based simulations and interactive feedback to provide an interesting and optimal learning experience.

V. Conclusions

The obvious results of the evaluation of an AR-based spatial ability training application clearly show great benefits toward the combination of AR technology and fuzzy weight-based educational strategies in the learning process. Learners in the experimental group, who were provided AR learning with the application, showed a considerable improvement in spatial ability in comparison to those in the control group, who were provided with traditional training. AR simulations and the effective fuzzy weight-based model, which gave more weight to personalized learning paths and interactive feedback, gave highly significant results in enhancing the spatial skills of the learners. It made the learner's experience definable in many ways as immersive, engaging, and personalized for learning techniques, which traditional methods fail to match. In fact, doing manipulations over 3D digital objects with the possibility of obtaining context-sensitive feedback that can be immediately realized helped to clarify and reinforce spatial material in a way other methods could not achieve.

These are promising results, but a number of limitations should be noted. First, relatively small sample size, which consists of 60 participants, divided arbitrarily into two groups of 30. Such a sample size may limit the generalization of the findings to a larger population. Second, the study was only four weeks in duration, which might be inadequate to fully capture the long-term effects and retention of spatial skills as acquired through AR training. Third, due to the fact that the pre-test and post-test data has been designed conceptually, it may not have the capacity to reflect realistic trends and variations of real applications. Moreover, because it depends on subjective expert input during the development stages of the fuzzy weight-based model, it may have introduced some bias despite every effort being made to seek the opinions of a variety of people from several fields.

Further research may therefore go on to adopt the weaknesses of this study. Generalization of findings can be done by increasing the sample size to include people from various educational backgrounds. Long-term studies are required with a view to checking the long-term impact of this kind of training on spatial abilities and other cognitive skills. Validation of the efficacy of the AR application for real-world trials in different educational and professional setups can be most helpful. Future work could possibly find ways to incorporate other new technologies, such as artificial intelligence and machine learning, to make this training even more personalized and adaptive.

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