Enhancing Higher Education English Learning through Virtual Reality and Game-Based Approaches Using the Fuzzy Deep Model

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Abstract. As mobile devices like tablets and smartphones become more popular, game-based education is gradually moving to mobile platforms. Game-based learning could easily facilitate English learning as opposed to classroom instruction and offers a comfortable setting by reducing the drawbacks of the typical classroom, which could arise from lower ratings for mental strain, lack of interaction, and fear of committing blunders. To handle learning complexities like ambiguity and vagueness in English, systems are built using fuzzy methods geared towards analyzing data and are typically implemented in situations where formal mathematical reasoning is either impractical or challenging. As a result, the new combination of fuzzy systems and deep learning model has given and shown how uncertainty may be effectively reduced by utilizing training fuzzy rules. This study adopted the Fuzzy-assisted Double Deep Q-Learning Network algorithm(F-D2QLN) to explore integrating mobile-based educational games into higher education English learning. The Takagi-Sugeno-Kang(TSK) Fuzzy Inference System(FIS) is used to overcome the difficulties of uncertainty, ambiguity, and imprecision inherent in natural language processing jobs to improve the decision-making process the Q-learning algorithm. By continuously learning and improving the learning process in response to the learner's performance and progress, double-deep Q-learning in game-based English learning aims to create an adaptive, personalized, and effective learning experience for each unique learner. The model's accuracy validates the effectiveness of the proposed scheme, Root Mean Square Error(RMSE) metric, and Retention Rate(RR) compared with existing approaches.

Keywords: Mobile and game-based learning English; Fuzzy Inference System; and Double Deep Q-Learning Network, virtual reality.
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1 INTRODUCTION

Virtual reality (VR) technology is a powerful tool that can enhance the effectiveness of Mobile game-based learning not only accelerates student learning in a fun way but also increases motivation among students; it has become a hot topic in current studies. Adults are more motivated to learn with educational video games when the objectives are clear and the procedure does not overburden them. Due to their usefulness and growing popularity in language teaching, educational games benefit students. As each student may have different strengths, it is advised to use all senses and incorporate every deviation as feasible while creating instructional games for adults. Although it has an adverse perception, learning from failures can be advantageous in deep learning.

In contrast to Boolean reasoning, where the truth value can either be accurate or untrue, fuzzy logic is concerned with models that manage the concept of partially accurate information. In randomized problems where the assessment is based on aspects of truthfulness and the results are created from potential and inaccurate data, fuzzy logic is so acceptable. The system may learn the best course of action in each state of the game-based learning environment using the double-deep Q-learning algorithm, a reinforcement learning technique. The system can adapt and customize the learning experience for each unique learner by altering the difficulty level of learning tasks and offering individualized feedback by continuously learning from the learner's engagement with the game-based learning environment.

The last ten years have increased interest and attention to gamification in educational activities due to its alleged advantages for learning and inspiration [14]. Computer game-based learning in higher education has been the subject of various studies. The cognitive area is represented by learning, behavior results, and either emotional consequences, inspirational results, or a combination [5]. The notion of "game-based learning" refers to the attainment of specific learning objectives through gameplay and subject matter, as well as the enhancement of educational experiences by including problem-solving scenarios and difficulties that give learners a belief in accomplishment [9]. Interactive multimedia games in English language instruction could be a useful strategy for enhancing the efficiency of conventional English programs while bringing life to them. Digital games for vocabulary learning are more successful than traditional teaching techniques [13],[4]. Anxiety frequently accompanies learning English ability, and it has an inverse relationship with stress factors [22]. Through various educational paradigms, including gamification, higher educational institutions (HEIs) foster healthy and environmentally friendly environments for students and professors [11]. The analyses of qualitative investigation revealed that digital educational games and mobile-based learning help students learn the English language and improve their college-level English competence [20]. Evaluation for teaching in higher educational institutions improves efficiency in learning and realistic English threshold, according to evaluation system feedback on the level of English learning ability by allowing a system for teaching intellect, the system for examination and validation, and a system for gathering input [9]. The authors in [12] employed fuzzy logic to determine the degree of player knowledge level uncertainty based on in-game ratings to guide the adaptation mechanism. The Fuzzy Logic (FL) method is rather sophisticated since it necessitates mapping language rules for processing data, similar to the cognitive process in individuals [15]. The hybrid technique combines fuzzy logic and Artificial Neural Networks to handle the complexity of learning English very well.

As a result, Adaptive Neuro-Fuzzy Inference System (ANFIS) is more suited for further purifying recognized learning outcomes of English learners by eliminating the fuzziness brought on by the elements provided in each game level [10]. The Fuzzy Analytic Hierarchical process with Genetic Algorithm (FAHP-GA) and Bidirectional Long Short-Term Memory (Bi-LSTM) techniques was utilized continuously based on the individual tastes of the learner to create procedural gaming levels [7]. The deep learning-based implication is made transparent by the induced fuzzy connections employing a shared set of semantic implications that are susceptible to interpretation by people [18]. An interval type-2 fuzzy neural network with a Gaussian membership function is proposed to investigate students' feelings of boredom with English learning. It identifies the emotions through the speech recognition of participants, but it lacks interaction and active participation of learners [22]. The deep learning model can be understood, and the deep network's reasoning ability for the learning model can be explained by using neuro-fuzzy architecture to handle non-linearities in the input of the fuzzification and defuzzification processes [19]. Existing deep learning approaches have flaws such as poor response effectiveness, uneven answers, and linguistic comprehension mistakes [24]. The built model may address the automatic scoring problem of the English translation by combining fuzzy semantics and text-fuzzy semantic resemblance to produce a suitable rating of participant feedback by combining deep conceptual and deep linguistic variables [1].

- A F-D2QLN is used in game-based English learning in higher education to increase the effectiveness and efficiency of the learning process.
- The TSK-FIS gives learners the deciding ability by gathering and analyzing the fuzzy uncertain information about the learning environment and their performance in a gaming environment.
- To create an adaptive, personalized, and effective learning experience for each unique learner by increasing their learning process Double Deep Q-Learning Netowork(D2QLN) is employed.
- The proposed system is validated by evaluating the statistical and classification metrics like mean, standard deviation, paired sample t-test, accuracy, RMSE, and retention rate calculation for improving higher education English learning.

The remainder of the work is structured as follows. In Section 2, the related work for the literature review is presented. Section 3 includes an overview of mobile and game-based interactive learning platform assisted with FIS-assisted D2QLN model implementation, and a discussion of its supporting modules are given. Section 4 shows metric evaluations of students' English learning motivation in higher education with clear dataset descriptions. Section 5 concludes the work with the advantages and limitations of the proposed scheme, followed by the future scope of the research work.

2 REVIEW OF THE LITERATURE WORK

Cheng et al. [3] applied Game-Based Learning(GBL) platforms like Quizlet to increase students' enthusiasm toward English learning in college 1st year and development of Test Of English for International Communication Vocabulary (TOEIC). The present investigation aimed to investigate 25 Taiwanese non-English significant higher education students' proficiency in TOEIC vocabulary development and English language acquisition through Quizlet. As a result, on the last day of the course, a 5-point Scale survey was created and given to each student. Results show that 93% of them reported feeling significantly more confident, and 97% of students Quizlet had considerably increased their motivation to learn TOEIC vocabulary. Due to its limited number of inputs dataset, it may not work better for many input samples.

Troussas et al. (17) elaborated an Interactive Fuzzy logic-based Guidance Recommender (IFGR), a personalized support system for the learners identifies and an intelligent learner modeler that supports the mobile and game-based learning system using Quiz Time focuses on the assessment of the learners' knowledge level in the language C#. The learners' knowledge is tested through the knowledge module, a vectorial-based recommendation module. Computer science professionals confirmed the application's suitability for educational usage, and students emphasized its value and favorable effects on learning. IFGR provides users with individualized recommendations according to their cognitive demands with evaluation for accuracy metrics reason, frequency, and type of erroneous outcome performed by users were evaluated.

Chen et al. [2] utilized a Mobile Game-based Virtual Reality (VR) English Learning System [MGVR-ELS] for student English learning performance, student gameplay enthusiasm, and autonomy in learning from an intellectual and behavioral approach, according to statistical findings, self-assurance, inherent value, and examination anxiousness substantially impacted game involvement and enjoyment. While assimilation and integration improved self-management, entanglement, development, and participation improved confidence in themselves. The result shows the evaluation of R, adjusted R^2 and Analysis Of Variance (ANOVA) test for evaluating student engagement and self-learning routine.

Yanes et al. [21] offered a novel multimodal fuzzy logic method for identifying English language learners through challenging games that combines cognitive analysis with ANFIS for learning. The information technology responses from learners were gathered using the Delphi technique after a Strengths, Weaknesses, Opportunities, and Threats analysis (SWOT) evaluation of the usage of video games to learn English. Positives, shortcomings, possibilities, and risks elements for input entries, and it forecasts the result through Learning possibilities of language by considering the effects of different input factor modifications. The FIS results show that minimum Root Mean Square Error (RMSE), Mean Square Error (MSE), and Mean Absolute Error (MAE) during validation with epoch numbers for an efficient learning process.

Ince et al. [8] Utilised Hybridized Bidirectional Long Short-Term Memory (Bi-LSTM) based Fuzzy Analytic Hierarchy Process-Genetic Algorithm (FAHP-GA) to create an adaptive dynamic gaming level with players' preferences in an optimal way for establishing the game dynamics of a new level, such as the question difficulties, which is the degree of complexity of the query that a player must correctly answer, Coin count that is displayed in the period for the player to gather and barrier count that is generated in the duration span for the player to navigate through without crashing or being trapped. The results show that the minimum RMSE error value of 0.39%.

Ref.no	*Technique used*	*Learning Platform*	*Data source*	*Performance evaluation metric*
[3]	*GBL*	*Quizlet-English &TOEIC vocabulary*	*25 first-year students*	*Post questionnaire feedback form*
[17]	*IFGR*	*Quiz Time – c#*	*A:20,B:80*	*ETest*
[2]	*MGVR-ELS*	*VR platform*	*274 students self-assessment.*	*Pre-test, post-test, t-test, and analysis of variance(ANOVA test)*
[21]	*ANFIS*	*Duolingo*	*Students -A questionnaire survey*	*SWOT Analysis (RMSE, MSE, MAE)*
[8]	*HBiLSTM-AHPGA*	*Educational games*	*Students-18[10M/8F]*	*Error rate, Flexibility, volume, balance, and accessibility*

Table 1: Literature study comparison of various algorithms.

According to the relevant literature, using mobile and game-based learning enhances outcomes for learning and inspires students to learn. Based on a thorough literature review, educational games' impacts on motivation, benefits, and limitations were also investigated for English learning. The existing algorithms used for comparison purposes are studied in a detailed manner described in Table 1, with necessary implementation for thorough field analysis. The reviewed algorithms are IFGR, MGVR-ELS, ANFIS, and HBiLSTM-AHPGA, with various game-based learning environments with different performance measurements. These algorithms still lack some of their work, which is rectified by implementing the solutions in the proposed F-D2QLN scheme.

3 PROPOSED SCHEME

The rise of mobile technologies presents opportunities to transform education by fusing game-based learning with mobile educational experiences. Games with animated graphics and soundtracks effectively encourage youngsters to acquire new words in languages. Interactive games can be successful instruments of teaching English that accelerate intentional learning among students. Good games should have a specific set of basic components to accomplish this. An interactive learning setting can offer useful data to examine as students learn. The technique is based on fuzzy logic and deep neural networks that are highly successful and functional under many rules and circumstances. The deep fuzzy model could also be used to customize the game to the preferences and skill levels of the player. Mixing fuzzy logic and deep learning model strategies into the game's architecture might employ a deep fuzzy model for game-based English learning. The model would be taught to recognize linguistic patterns and structures after being trained on a dataset containing English language data, such as text, audio, or images.

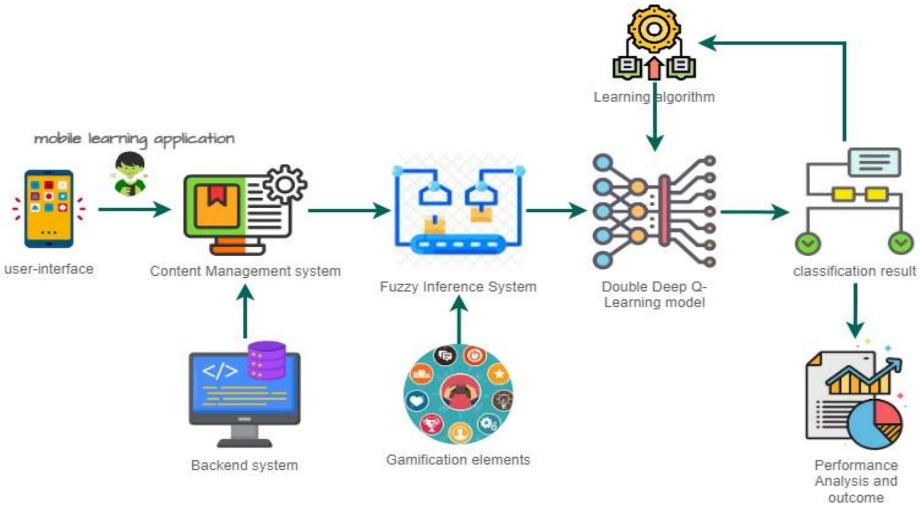

Figure 1: System architecture diagram of the proposed scheme.

Figure 1 illustrates the proposed system architecture of the F-D2QLN algorithm as mentioned above; the main idea of the proposed work integrates the benefits of deep learning, fuzzy logic, and game-based learning to provide students with a fun and engaging way to learn English while simultaneously providing accurate and understandable feedback to help them improve their language abilities. The fuzzy values are then sent via some deep neural network-based hidden layers. Each hidden layer is responsible for picking up on various aspects of the data, including word logic, part of speech, grammatical conventions, and vocabulary. Lastly, the performance analysis and student outcome in the output layer give feedback about the student's engagement in the mobile and game-based English learning platform. Depending on how accurately the learner responded, this feedback might take the form of game feedback, such as points, badges, or awards.

3.1 English Learning Systems and Game Accessibility

User interface: A mobile app is one of the most popular tools for learning English. The user accesses the game using mobile application software, where the game's interface and graphics should be made user-friendly on mobile devices. User interaction occurs through this interface and might contain the game's initial screen, the number of phases, tasks, and tools for monitoring advancement, ranking players, and offering feedback. The content management system procedure must be evaluated in the next process to maintain communication with the mobile and enable the learning process continuously.

Content management system: In this content management procedure, the user engages with this content directly, whether it be reading passages, listening to audio files, or watching videos of lessons to educate English; the game may employ a range of media formats. The content management system manages the game's content, including the questions, solutions, pictures, and audio. The information should be easily customizable and updated thanks to the content management system's versatile and user-friendly architecture. It needs the backend database support for evaluating the information records about the learning process and students in the gaming environment about various elements of vocabulary, reading, proficiency skill, and comprehension level.

Backend system: The user's data, including learning materials, performance metrics, and progress reports, are stored in this component. The student's information, including performance history, learning goals, and preferences, is kept in a database. The database should be created with scalability, security, and the ability to manage and retrieve data quickly in mind. The backend system involves specific working elements like editing a question: This aspect is important since it relates to how teachers create their evaluation materials. More particularly, it incorporates traits that can help create evaluation materials in such scenarios. Evaluation Method: This aspect relates to the support in gathering the evaluation materials. Minimizing the time and effort required to gather this information is the ultimate objective of this dimension. Examination and Answer Analyses: This dimension focuses on gathering information on how the learners engage with the system, including the amount of time required to provide an answer, the quantity and nature of errors, etc.

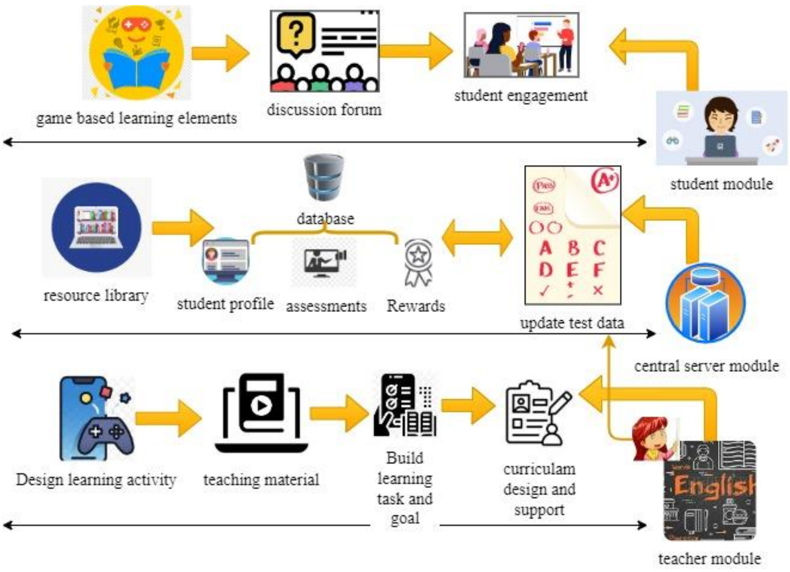

Figure 2: The diagrammatic representation of game-based English learning module separation.

Figure 2 shows the teacher-student module components integrated into the central server for gaming interaction. The teacher can do research and choose appropriate applications and games that fit the course's learning objectives and curriculum. Age-appropriate, entertaining games and apps that allow students to use and practice their English language abilities are necessary. Using tests, quizzes, and other assessment resources within the game-based learning platform, the teacher may keep track of student modules and evaluate the student's progress. Additionally, the teacher can assess the efficiency of the game-based learning strategy and modify the curriculum or learning activities as necessary. The central server module manages the backend support of the gaming platform for English learning and stores students' performance records throughout the evaluation process. In mobile and game-based English learning, the teacher's job is to facilitate and promote the learning process while giving students advice and feedback as they advance through the course.

3.2 Gamification Elements to Improve Learners' Engagement in a Gaming Environment

Gamification features are included to increase the learners' engagement, motivation, and enjoyment of game-based English language learning. By finishing the game's objectives or activities, students can accumulate points and rewards. The game can use these awards to open up additional characters, levels, or features. These components may include leaderboards, feedback and progress tracking, points, and incentives. Badges and achievements are also considered as gamification involvement, where the students can complete their particular challenges or game milestones and receive badges and achievements. These badges can visually show the learner's development and accomplishments.

3.3 TSK-FIS Scheme for Decision-Making in the English Learning Process

By modeling the link between the data entered, such as the user's success in the game and the degree of complexity of the game and the output referred to as the student's level of English competence or proficiency, the TSK (Takagi-Sugeno-Kang) fuzzy inference system can be utilized for game-based English learning. The fuzzification procedure, IF-THEN fuzzy rules, and defuzzification method are the three elements that make the overall fuzzy classifier.
Step 1: Define the entered variables that will be utilized to describe the English proficiency of the user. Variables such as pronunciation, vocabulary, grammatical structure, and so on may be included.
Step 2: Fuzzification: Employing fuzzy expressions from languages and membership functions, an accurate array of input values is fed into the model and transformed into a fuzzy set.

$$\mu(x) = max(min((x-a)/(b-a),(c-x)/(c-b)),0) \tag{1}$$

The input values are transferred to fuzzy sets using membership functions. A triangular set of fuzzy values with variables $a, b, and\ c$ has the following membership function as shown in equation 1.
Step 3: Create a knowledge base compilation of fuzzy rules that maps the fuzzy sources to the fuzzy output using expert knowledge or based on information methodologies. These rules usually appear in the style of "IF-THEN" statements, with the predecessor being a set of fuzzy inputs and the result being a set of fuzzy outcomes, as given in Equation 2.

$$y = w_0 + w_1x_1 + w_2x_2 + \ldots + w_nx_n \tag{2}$$

Where the $w_0, w_1, w_2 \ldots. w_n$ represents the attributes that are acquired during the training period.
The fuzzy rule set for the input of inference systems for game-based English learning

1) IF (pronunciation is low) AND (comprehension is low) AND (reading is low) AND (vocabulary is low) AND (proficiency is high) THEN (Score is low)
2) IF (pronunciation is poor) AND (comprehension is poor) AND (reading is poor) AND (vocabulary is strong) AND (proficiency is moderate) THEN (score is moderate).
3) IF (pronunciation is low) AND (comprehension is low) AND (reading is low) AND (vocabulary is high) AND (proficiency is high) THEN (score is high)

Step 4: Decision-making inference engine: Given a set of rules, it links an input parameter to an output. Mini-batch SGD can be a relatively cheap and efficient approach for estimating rule parameters in TSK fuzzy inference systems for game-based English learning. Still, it involves accurate adjustment of the hyperparameter settings and oversight of the optimization procedure to achieve its optimum performance. Divide the initial training data into fixed-size mini-batches. Calculate the output of the TSK fuzzy inference system for each mini-batch using the present rule following parameters. Utilise backpropagation to determine the Mean Square Error (MSE) gradient about the rule-following parameters.
Step 5: Defuzzification: Using memberships processes, the resultant output that is fuzzy is converted to a crisp result. The rule outputs aggregate the fuzzy outputs, and a defuzzification process produces a crisp result. The weighted average defuzzification is a popular approach that is defined in equation 3:

$$y = \sum(w_i * x_i) / \sum w_i \tag{3}$$

Where w_i represents the weight associated with the rule i and x_i denotes the crisp output for the same fuzzy rule.
Step 6: Output: Using the clear result produced in the previous step, update the user's English proficiency score. Continue to keep a close watch on the user's performance and, as needed, modify the fuzzy rule base and variables to raise the system's accuracy.
Fuzzy Inference Systems (FIS) can be linked with D2QLN for game-based English learning To enhance the algorithm's performance and offer a more flexible learning environment. FIS is an effective method for dealing with ambiguous and ambiguous data, which is frequently the case in activities involving the processing of natural languages, such as learning English. The FIS is integrated with D2QLN to estimate the learner's state based on their success in the game. A collection of linguistic rules that translate input factors like the English learner's accuracy and reaction time to linguistic values like "good" or "poor" can be used to train the FIS. The FIS produces a collection of linguistic factors that can change the game's complexity or provide the player with specific feedback.
Figure 3 shows the working module of TSK-FIS input in the D2QLN algorithm is then given the FIS output as an additional input, which can aid the algorithm in better determining the best course of action to take given the learner's current state. For instance, the D2QLN algorithm can modify the game to offer extra opportunities for practice if the FIS produces a linguistic variable indicating that the learner is having trouble with a specific grammar rule.

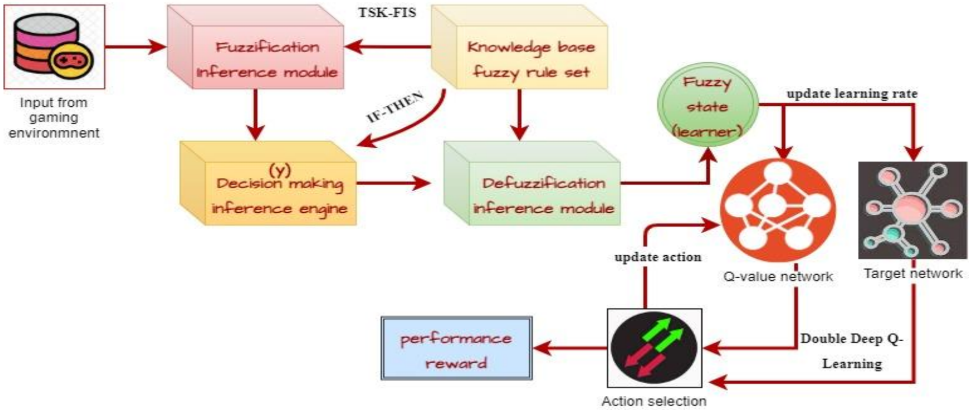

Figure 3: Working module of TSK-FIS in D2QLN algorithm.

3.4 D2QLN Algorithm for Supporting Personalized Learning Process for English Learners

With the current state of the environment in the game as input, a neural network is used to estimate the Q-values of all feasible actions. During the training phase, the neural network's weights are adjusted based on the replay buffer's experiences. That allows the system to improve its gameplay judgments by learning the best Q-values associated with every state-action pair. This game component learns the best action-value function using two neural networks, Q_online and Q_target. While Q_target is used to predict the value of the subsequent state, Q_online is used to choose actions based on the present and learner's state. With the addition of data from FIS, the Q-values are updated using the specific Q-Learning method. To increase stability and lessen the overestimation of Q-values, the weights of the Q_target network are periodically updated with those of the Q_online network. The learners' real test or assessment scores could serve as an outcome or target variable, and data on their gaming behavior could serve as predictors.

3.5 The Trade-Off Between Exploration and Exploitation

The game agent (learner) must strike a balance between the requirement to exploit known behaviors of those with high Q-values and are likely to produce a positive reward in the assessment and the need for the agent to explore novel actions and learn from them. More specifically, the code first determines whether a random number generated between 0 and 1 is lower than the exploration rate during the training loop before choosing an action for the agent to do. Epsilon-greedy strategies are a popular algorithm technique that uses reinforcement learning to implement the exploration-exploitation balance. The algorithm chooses the best learning action with probability $(1 - \epsilon)$ in this strategy and chooses an arbitrary action with the rate(ϵ). Exploits typically have a low chance of exploring, whereas epsilon denotes the probability of deciding.

if random(val)< ϵ:

use random action

else:

update current-best action

In that case, the agent chooses a random action from a list of possible actions. Otherwise, the agent chooses the course of action with the highest Q-value, utilizing the previously learned Q-values.

3.6 Learning Algorithm

A variation of the well-known reinforcement learning algorithm Q-Learning is utilized in the Double Deep Q-Learning Network (D2QLN) algorithm. Through the process of "Q-Learning," a learner learns how to respond in a given educational game environment to maximize the cumulative reward signal for the performance outcome of the student based on various input categories, vocabulary, proficiency, reading, and comprehension. The neural network's weights are randomly initialized at the start of training and then subsequently updated to more closely resemble the real Q-values of the gaming environment. The learner accomplishes this by keeping track of an assessment table of Q-values in a database —estimates of the expected reward for performing a specific interactive assessment action in a particular game state. The D2QLN's algorithm is an effective tool for learning the best decision-making strategies when the best course of action might not be immediately apparent.

Algorithm: Fuzzy assisted Double Deep Q-Learning Network(FD2QLN)

1. Set up the DDQN model with arbitrary weights and create fuzzy sets and linguistic variables as the basis of the TSK-based FIS.

2.Initialize the necessary hyperparameters learning_rate, exploration_rate, batch_size, max_eps.

3. for every iteration episode in the range (num_episodes):

Game environment reset

Initial_state = environment in a game

total_reward =0.

Check base exploration (ϵ) speed on the current iteration episode.

Apply TSK-based FIS to each state to activate the language environment

Choose the action using the epsilon-greedy strategy, and update the highest Q-value.

update(action) = next_state, reward, done

end for

4.total_reward= total_reward+ reward

5. Adapt the exploration rate to the most recent episode.

The procedure can learn to make more accurate decisions over time, resulting in higher performance and learning outcomes, by iteratively modifying the Q-values based on observations from the environment. The learner eventually transitions from exploration to exploitation state as he learns more about the educational game outcome and accumulates the experience of learning English. The above algorithm can enhance the learning outcome of individual English learners in higher education based on their current state of action.

3.7 Classification Result

Classification in game-based English learning aims to give students quick, precise, and usable feedback so they may keep honing their language abilities through gameplay. In game-based English learning, the fuzzy-based D2QLN algorithm produces classification results with a set of Q-values that represent the estimated value of each potential action in light of the learner's current position in the game. Based on a set of fuzzy criteria that consider the degree of membership to each activity, these Q-values are then utilized to decide the appropriate action to execute. Given that it considers the learner's prior experiences and game incentives, it can give the learner more precise and personalized feedback. Given that the algorithm is created to adapt and learn from the student's interactions with the game, this can aid the learner in improving their language skills more quickly and effectively. Based on their performance against preset criteria or metrics, learners' responses to a given task or activity can be categorized using the TSK fuzzy inference system. The classification results can then be used to modify the game's difficulty level or give the student individualized feedback to aid in developing their language abilities.

3.8 Performance Analysis and Outcome

Various indicators, including accuracy, completeness of responses, the complexity level of games, and learner skill levels, can be used for performance analysis. The student's performance in various language abilities, such as grammar, vocabulary, pronunciation, or understanding, can be assessed using these metrics. Depending on the architecture of the game and the unique learning objectives, performance analysis can be done offline or in real time. This component keeps tabs on the student's

performance, choices, and achievements, and the game's design can be improved using this information, and consumers can receive customized suggestions. Teachers and parents can check that their students are ready for the enjoyable process of learning to read and write by using online games. A performance report that includes feedback for both the learner and teacher can be produced once the learner's performance has been examined. The learner's overall performance can be summarised, their proficiency in specific language skills can be broken down, their strengths and shortcomings can be listed, and they can receive individualized recommendations for progress.
The summary of the proposed scheme is by incorporating a TSK-based fuzzy inference system into the Q-learning algorithm, and the system can customize and adapt the learning experience for each unique learner by adjusting the learning rate, offering feedback, and adjusting the difficulty level of learning tasks following the learner's performance within the game-based learning environment. Educational games improved the higher educational English competence and learning attitudes of students. Combined with these two approaches, they can give a more robust and effective technique for game-based English learning. The system can adapt and customize the learning experience for each unique learner by altering the difficulty level of learning tasks and offering individualized feedback by continuously learning from the learner's engagement with the game-based learning environment.

4 EXPERIMENTAL EVALUATION ANALYSIS

4.1 Process of Gathering and Analyzing Data

The task-based methodology using a digital game in a flipped educational setting, a model for teaching English verbal communication abilities, was created by combining all three linguistic strategies: task-based instruction, digital game-based language learning, and flipped education. An experimental study on English verbal communication competence was carried out over 13 weeks with 23 second-year nursing students at a private institution in Thailand using a one-group previous test & the post-test design[26]. Inferential statistics (paired-sample t-test) and descriptive statistics (mean and SD) were used to analyze the participants' results. The quantitative results demonstrated that the participants' mean post-test scores on all aspects of oral communication, including task completion and language materials, observing comprehension, word pronunciation, and proficiency, were statistically greatly higher than their mean pre-test scores ($p < 0.05$). The quantitative information obtained from the closed-ended questions in the opinion questionnaire was analyzed using descriptive statistics (mean and SD). In contrast, the qualitative information obtained via the open-ended inquiries in the opinion survey and that from the semi-structured interviews was analyzed qualitatively through game-based English language learning techniques. A test taker's rating has been rated from the Likert scale with a range of 0 to

4.2 Results and Discussion

4.2.1Calculation of mean and standard deviation

The mean, or an average, summarises variables or observations and measures central tendency. It is calculated by adding all the values and dividing the total number of values by the total range. Equations 4 and 5 define the mean and standard deviation as follows:

$$mean(\mu) = (sum\ of\ all\ scores) / (number\ of\ total\ scores) \tag{4}$$

$$\sqrt{\frac{(sum\ of\ (each\ score - mean)2}{(total\ number\ of\ scores - 1))}} \tag{5}$$

The term sum refers to the total of all ratings in the sample, and the $number\ of\ total\ scores$ refers to the total number of scores in the sample. The term $mean$ refers to the sample's average score, while 2 means squared term.

Game feedback aspects	*Rating comments*			*Mean (μ)*	*SD*
	R1	*R2*	*R3*		
Grammar and spelling are correctly taught in the educational material.	*5*	*5*	*5*	*5.0*	*0.70*
The gaming activities are suitable for pre-task exercises that help learners activate their prior learning.	*4*	*5*	*5*	*4.7*	*0.50*
The game gives players numerous options for interacting.	*5*	*5*	*5*	*5.0*	*0.70*
The game encourages language acquisition in the player	*5*	*5*	*4*	*4.7*	*0.50*
The course material sufficiently covers the goals and objectives of learning.	*4.5*	*4.5*	*5*	*4.7*	*0.50*

Table 2: The game-based English learning called "Cool Nurse" has been validated and evaluated by sample rating-based questionnaire samples.

Table 2 discusses the English oral communication test validation and evaluation of students' performance. Both the pre-test and post-test results for the students were videotaped. Three raters (the researcher, a native-English English teacher, and a native-Thai English teacher) evaluated the student's performance on the pre-and post-test using the analytical rating scale to assess language skills.

Mean value	*Interpretation and evaluation*
0-0.9	*Negative*
1-1.9	*Less Negative*
2.0-2.9	*Average / Neutral*
3.0-3.9	*Positive*
4.0-4.9	*Highly positive*

Table 3: The interpreted result of the mean score result of the game-based English language learning questionnaire.

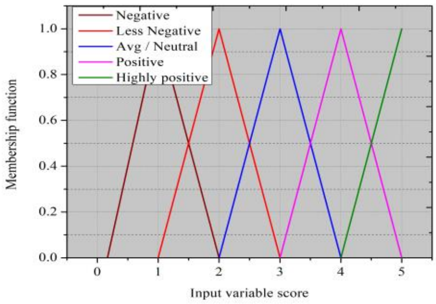

Figure 4: Plotting of fuzzy membership function based on input rating score.

Figure 4 illustrates the fuzzy membership function for the student's interaction level based on the rating score of the semi-structured questionnaire survey taken in the game-based English learning environment. The input rating score ranges from 0 to 5, with appropriate interpretation results from Table 2. The membership value reaches 1 with the closest result of the score reached and given by the participant input. If the game aims to teach vocabulary, the input factors could include the word's complexity level, routine usage, and connotation. The score or ratings of the degree to which the player knows the word might be an outcome factor.

A paired t-test is a statistical analysis that contrasts two matched or related samples. A parametric test called the paired t-test is utilized to evaluate if the mean difference between two similar samples is statistically significant. In addition, the test determines the degrees of independence, which are determined by dividing the number of pairs by one, as given in equation 6.

$$t-test = \frac{(mean\ difference - hypothesised\ difference)}{(standard\ deviation\ of\ the\ variance\ /\ \sqrt{number\ of\ \ pairings}} \tag{6}$$

While the $mean\ difference$ refers to the average variation among the sample pairings. "Hypothesised difference" refers to the difference between the two populations' means. The "standard deviation of the variations" refers to the difference in standard deviation among the pairs of samples. "several pairs" refers to the total sample.

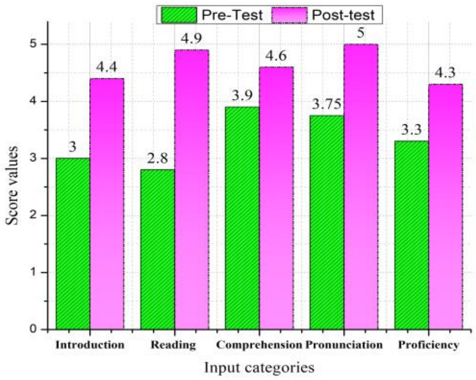

Figure 5: The average scores on every single aspect of the students' pre-test and post-test.

Figure 5 shows that the post-test mean scores on all input aspects were higher than the pre-test average sample scores from the input data source [6]. The pre-and post-oral interaction test recordings were transcribed and qualitatively analyzed to determine what improvements or changes people had made in their verbal communication ability after participating in the game-based English learning based on the various input categories to balance and improve the reliability of results from the oral communication tests. Excerpts of their pre-test and post-test transcripts were chosen from the values observed in the [6] to compare and show the growth of each set of participants. The findings were explained within the context of the rating scale's components, which included task achievement and linguistic resources, as well as comprehension, pronunciation, and proficiency.

4.3 Root Mean Square Error (RMSE)

In setting up a mobile and game-based English learning system, equation 7 defines the RMSE that can be used to assess the system's accuracy in forecasting learners' competence levels based on their knowledge background

$$RMSE = \sqrt{\frac{1}{N} * sum(learner\ proficiency\ \widehat{level - }\ actual\ target\ variable)^2} \quad (7)$$

Where N denotes the total number of learners in the dataset.

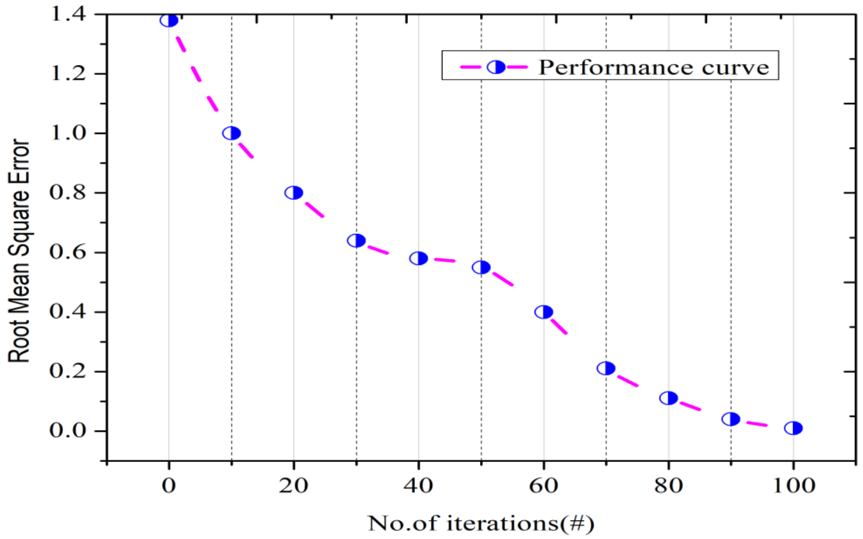

Figure 6: RMSE graph comparison performance of the proposed algorithm with various iterations.

Figure 6 demonstrates that the performance of the proposed algorithm gives the minimum number of RMSE when performing game-based English learning interpretation. First, to compute the RMSE for a game-based English learning system, establish the target variable and learner proficiency level and gather data on the target variable's expected and actual values. The student performance assessment based on interactivity and ratings given for each survey questionnaire integrated with the level of efficiency the participant attained is plotted. The comparison criterion is the root mean square error generated by training and verification data. A lower RMSE number often indicates better forecast accuracy of the proposed algorithm for improving English learning efficiency in the gaming environment.

4.4 Retention Rate(RR)

The retention rate is a popular metric used to assess how long learners stick with a game-based English language learning program. The following equation 8 defines the retention rate formula:

$$Retention\ rate\ = ((A)\ /\ (B))\ \times 100 \quad (8)$$

Where A number of students who continue to participate in the program over a certain time and the total number of students who first participated in the program is given as B, the retention rate for a game-based English language learning program is depicted in the following sample graph as it changes over the change in several weeks is shown in Figure 7.

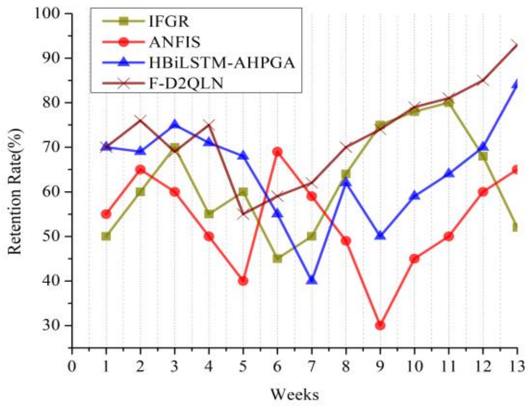

Figure 7: Students Retention rate comparison with different algorithms.

A game-based English language learning program's retention rate that goes up is generally seen as a success. A greater retention rate shows that students are more interested in the curriculum and are more likely to stick with studying and advance over time. The retention rate of students in the course has been evaluated for 13 weeks program. Better learning outcomes, better results on language proficiency exams, and more student satisfaction may result. Higher retention rates can also save money on marketing and hiring new students, among other advantages. The proposed Fuzzy assisted D2QLN algorithm's retention rate is higher than other existing algorithms IFGR, ANFIS, and HBiLSTM-AHPGA.Compared to existing approaches, students were shown their interest in current mobile and game-based English learning environment implementation using the proposed scheme.

4.5 Accuracy (%)

Accuracy can be measured as the percentage of students accurately classified when classifying English language learners into various competence levels based on their performance in the game-based learning environment. The proposed F-D2QLN model's capacity to make wise choices that result in greater game rewards can be used to evaluate the accuracy given in equation 9.

$$Accuracy = (Number\ of\ correct\ decisions) / (Total\ number\ of\ decisions) \quad (9)$$

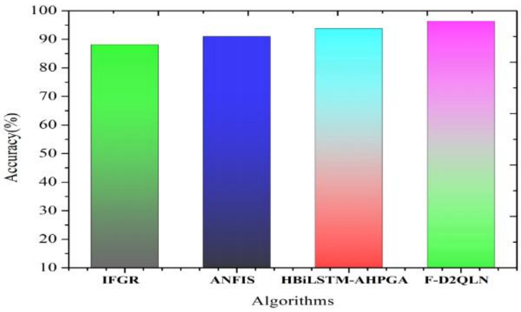

Figure 8: Accuracy comparison of various algorithms.

Figure 8 shows the accuracy results from a comparison between various algorithms. The proposed scheme gives the highest accuracy in student progress monitoring and tracking the learning outcome based on their current interactivity towards the action of the gaming field. The accuracy would be 95.6% if there were three competency levels (beginning, intermediate, and advanced), and the model accurately identified 95 out of 100 learners. Some right decisions divided by the total number of decisions equals accuracy is shown in Figure 8. The other existing algorithms show lesser accuracy in detecting student performance evaluation which leads to poor performance of the model.

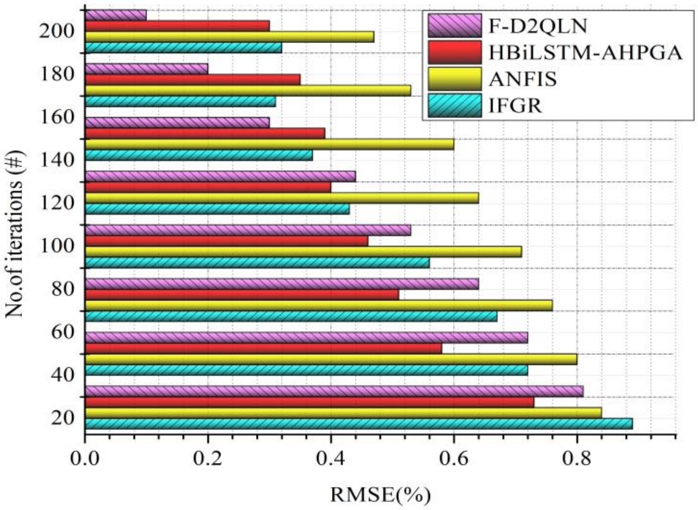

Figure 9: RMSE graph comparison of various algorithms with different iterations.

Figure 9 explains the implementation of RMSE graph comparison for various algorithms with the proposed scheme F-D2QLN. The graph shows that the error range of the proposed algorithm reduces when the number of iterations increases. The complexity of the environment, the number of fuzzy rules, the number of learning episodes, the size of the neural network architecture, and the number of hyperparameters employed are some variables that might affect the RMSE outcome of an FDDQN network. The accuracy of the Q-value in the proposed algorithm can be assessed using RMSE and gives the best result of 0.1% compared to IFSR, ANFIS, and HBiLSTM-AHPGA.

The performance efficiency of the proposed F-D2QLN algorithm is discussed with the numerical results discussed by using game-based English learning to enhance students' general verbal communication abilities as listening comprehension. The resulting graph proves the level of student learning engagement raised, with greater retention and accuracy range. The fuzzy combined with deep learning model works very well in educational mobile and game-based English learning. The proposed scheme outperforms the existing algorithms in terms of learning involvement and motivation toward an interactive learning environment.

5 CONCLUSION

Virtual Reality (VR) can be a valuable addition to Mobile game-based learning has proven to be a successful strategy for teaching students first. It promotes knowledge, according to which students build knowledge by engaging in experiences and evaluating those encounters. A Fuzzy-assisted

Double Deep Q-Learning Network is used in game-based English learning to increase the effectiveness and efficiency of the learning process, The difficulties of uncertainty, ambiguity, and imprecision that are inherent in natural language processing activities, such as English language learning, are specifically addressed by the fuzzy logic system. The system is trained to make the best judgments depending on the feedback from the game-based learning environment using the double-deep Q-learning network, a reinforcement learning algorithm. Students taught through games exhibit good attitudes regarding learning and may show greater interest in it. The main advantage of the F-D2QLN is that it provides personalized learning and enhanced engagement and can adjust the complexity level of learning tasks based on learner performance. A few ideas for future scope are also given based on the proposed scheme implementation. Future research will consider students' sociological behavior and English learning based on emotional preferences to determine how much they value collaborating with others and tailor the classroom atmosphere to suit their interests. It could improve our application's pedagogical effectiveness even more.

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