# FEEDBACK-DRIVEN ADAPTIVE ENGLISH LANGUAGE LEARNING FRAMEWORK THROUGH HIDDEN ENGAGEMENT PATTERN ANALYSIS USING CGSPQLearning AND GH-Fuzzy

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*Received: Mar. 10, 2026; Accepted: Apr. 14, 2026*

English is widely used globally, but traditional methods fail to analyse hidden engagement patterns, leading to inaccurate interpretation of learner behaviour. Hidden engagement reflects implicit interactions that distinguish productive learning, involving active participation and measurable improvement, from passive usage with limited outcomes. To address this, a feedback-driven adaptive English learning framework is proposed using GH-Fuzzy and CGSPQ-Learning. The process begins with data collection, preprocessing, augmentation, and attribute extraction, followed by learning plateau detection and interrelationship analysis. GH-Fuzzy is employed to analyse hidden engagement patterns and differentiate learner behaviours. Student improvement is then classified using IQBiSLSTM for enhanced stability and efficiency. Finally, CGSPQ-Learning generates personalized feedback to improve learning outcomes. The proposed model outperforms existing methods, achieving improved performance with reduced rule generation time.

**Keywords:** Feedback-Driven Model, Adaptive English Language Learning, Productive and Passive Learning, Student Improvement Classification, Hidden Engagement Pattern Analysis, Deep Learning (DL), and Learning Plateaus Detection.



http://dx.doi.org/10.6180/jase.202609_32.073

## 1. Introduction

In recent years, the importance of learning the English language has continued to grow globally, serving as the primary medium for education, communication, and professional development across countries (Lei et al., 2022) [1]. Therefore, there is an increasing demand for effective and personalized English language learning systems that support learners with diverse backgrounds, proficiency levels, and learning goals (Ni & Cheung, 2023) [2] (Lawrence et al., 2024) [3]. Particularly, for beginner learners, continuous participation supported by engagement-aware feedback enables gradual skill development and sustained proficiency improvement, thereby contributing to long-term language learning outcomes. However, the conventional works primarily rely on observable outcomes such as test scores and task completion rates, leading to inaccurate classification of student improvement (Hossain, 2024) [4]. Such approaches fail to capture underlying learner behaviors such as effort consistency, interaction patterns, and cognitive engagement, which are critical for understanding true learning dynamics. As a result, outcome-based evaluation alone provides a limited view, motivating the need for engagement-oriented analytical frameworks (Gayed et al., 2022) [5]. ML and DL methods have shown promising results in content adaptation and performance prediction. However, they often function as black-box models with limited explainability (Annamalai et al., 2023) [6] (Al-khresheh, 2024) [7]. Traditional methods fail to analyze hidden engagement patterns and lack explainability, while the proposed framework integrates GHFuzzy, IQBiSLSTM, and

CGSPQ-Learning to enable transparent, feedback-driven adaptive learning with improved personalization.

### 1.1. Research Overview

In this section, the main limitations of the traditional works and the objectives of the proposed model to overcome such limitations are elaborated.

Research Gap: None of the existing works analyzes hidden engagement patterns that distinguish proactive learning behaviors from passive or disengaged usage. This condition leads to accurate decision-making for improving student performance in English learning.

Problem Statement: The limitations of the traditional works in demonstrating the English learning model are listed as follows,

- Despite having longitudinal usage and performance data, many prevailing systems fail to detect stagnation or plateauing in learning progress.
- Most of the conventional works failed to analyze the interrelationship of Age, Gender, and motivation, resulting in inaccurate learner profiling and limited personalization of adaptive English learning systems.
- These demographic attributes statistically influence beginner engagement patterns, affecting interaction behavior, learning consistency, and feedback responsiveness, thereby supporting structured behavioral-demographic analysis.

Most of the existing work lacks explainability in adaptive English learning systems, reducing trust, hindering prediction systems, and limiting the personalization of traditional English Language Learning models.

Significance and Scope of this Study: The proposed framework integrates GH-Fuzzy, CST, IQBiSLSTM, and CGSPQ-Learning to enable explainable, feedback-driven adaptive English learning through effective engagement analysis, improved classification, and personalized feedback.

Research Aim and Objectives: The main aim of the proposed work is to develop a feedback-driven adaptive English language learning model while evaluating students' improvement. The objectives of the proposed work are listed as follows,

To efficiently differentiate whether the student is a proactive or passive learner, the hidden engagement patterns are effectively analyzed using the proposed Gaussian Hesitant Fuzzy

To accurately detect the learning plateaus, the proposed GH-Fuzzy is applied.

To effectively identify the interrelationships of students' age, gender, and motivation level, the Chi-Square Test (CST) is used.

To provide a deep explanation of the predicted outcome, the performance of the adaptive English learning system is enhanced using the proposed SHapely Kaniadakis Additive exPlanations (SHKAP).

The structure of the papers is demonstrated as follows: Section 2 illustrates the literature survey, Section 3 depicts the proposed methodology, Section 4 indicates the result and discussion, and Section 5 concludes the proposed work with future commendation.

## 2. Literature survey

(Chen et al., 2022) [8] proposed an AI and virtual reality-based English learning model with robot-assisted interactions, which improved engagement and interactivity but failed to detect learning stagnation, affecting improvement classification accuracy. The studies show that AI-driven models capture behavioral, cognitive, and emotional signals to better distinguish active and passive learning, improving adaptive decision-making. Ganesan et al. (2025) [9] proposed a VAE and Sparse Autoencoder-based framework for anomaly detection, achieving high accuracy and outperforming traditional models while reducing false positives. (Ma et al., 2025) [1] developed a DL and NLP-based adaptive English learning system using BiLSTM for personalized outputs, but its black-box nature reduced trust and interpretability. Recent advancements use transformer and deep learning models to dynamically personalize content based on learner behavior, improving adaptability and real-time optimization.

## 3. Proposed methodology for improving feedback-driven adaptive english language learning through productive and passive learning differentiation

This section presents the proposed framework for adaptive English learning through feedback analysis, aimed at distinguishing productive and passive learning behaviors, as illustrated in Fig. 1.

### 3.1. Data Collection

Initially, data ($D^{a}_{\mathrm{Col}}$) including student demographics (i.e., name, age, gender, etc.) and their learning outcomes are collected from publicly available sources to train the improvement classification model.

$$D^{a}_{\mathrm{Col}} = \left\{ D^{1}_{\mathrm{Col}}, D^{2}_{\mathrm{Col}}, D^{3}_{\mathrm{Col}}, \cdots, D^{\bar{a}}_{\mathrm{Col}} \right\}; a = 1 \rightarrow \bar{a} \quad (1)$$

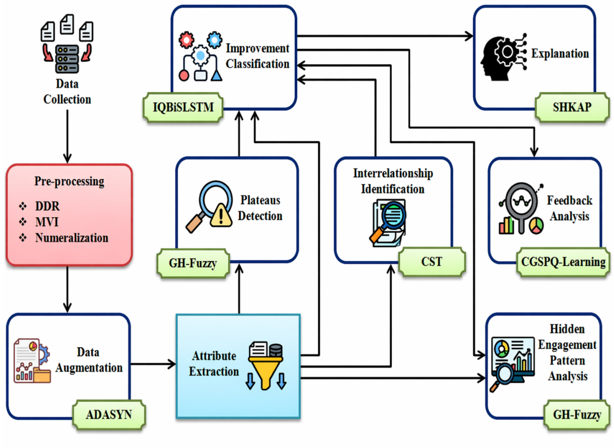


**Fig. 1.** Structure of the Proposed Work

Where, $\bar{a}$ illustrates the number of $\left(D_{\text{Col}}^{a}\right)$.

### 3.2. Pre-processing

Further, $D_{\text{Col}}^{a}$ contain duplicate entries, missing values, and irrelevant characters, affecting the data quality during student performance classification. Therefore, preprocessing regarding Data Duplication Removal, Missing Value Imputation (MVI), and Numeralization are performed.

### 3.3. Data Augmentation

Now, $D_{\text{Pre}}^{b}$ includes a limited number of data samples, leading to a biased outcome in classifying the student's improvement during English language learning. Therefore, the data augmentation is performed to increase the data samples using the Adaptive Synthetic sampling (ADASYN). ADASYN addresses class imbalance by generating synthetic samples for underrepresented engagement patterns, focusing on difficult regions to preserve data distribution and reduce bias.

### 3.4. Attribute Extraction

After data augmentations, the attributes that are necessary for the accurate classification of students' improvement in vocabulary, speaking, and reading of the English language are extracted from $D_{Aug}^{C}$. The extracted attributes $\left(D_{Att}^{d}\right)$ include student ID, age, gender, prior English proficiency, learning style, motivation level, time spent on the platform, platform usage frequency, vocabulary pre and post, reading comprehension pre and post, and speaking pre and post.

### 3.5. Learning Plateaus Detection

Now, from $D_{Att}^{d}$, Learning plateaus are detected using the proposed GH-Fuzzy to identify stagnation in learner performance, where the Gaussian Hesitant membership function reduces tuning complexity and ensures smooth mapping of input features. Initially, from $D_{Att}^{d}$, the learning plateaus are accurately detected based on the average learning gain $\left(G_{\text{avg}}\right)$, time spent $\left(T_{\text{spe}}\right)$, and usage frequency $\left(F_{\text{usg}}\right)$ of students during English language learning sessions. Here, the average learning gain is computed by measuring the vocabulary gain $\left(g_{voc}\right)$, speaking gain $\left(g_{spe}\right)$, and reading gain $\left(g_{rea}\right)$.

$$G_{avg} = \frac{g_{voc} + g_{spe} + g_{rea}}{3} \tag{2}$$

$$g_{voc} = V_{post} - V_{pre} \tag{3}$$

$$g_{spe} = S_{post} - S_{pre} \tag{4}$$

$$g_{rea} = R_{post} - R_{pre} \tag{5}$$

Where, $\left(V_{\text{post}}, S_{\text{post}}, R_{\text{post}}\right)$ illustrate the post (i.e., after intervention) score value for vocabulary, speaking, and reading, respectively, and ( $V_{\text{pre}}, S_{\text{pre}}, R_{\text{pre}}$ )indicate the pre (i.e., before intervention) score value for vocabulary, speaking, and reading, correspondingly. Now, $\left(G_{\text{avg}}, T_{\text{spe}}, F_{\text{usg}}\right)$ are converted into fuzzy sets( $\widehat{F}_{inp}$ ) through defuzzification using the GH membership function ( $m_{GH}$ ).

$$\left(G_{\text{avg}}, T_{\text{spe}}, F_{\text{usg}}\right) \xrightarrow{m_{GH}} \hat{F}_{\text{inp}} \tag{6}$$

$$m_{GH}(F_{\text{inp}}) = \begin{cases} \exp\left[-\dfrac{(F_{\text{inp}} - v_1^{\text{cen}})^2}{2(\sigma_1^{\text{sd}})^2}\right], \\ \exp\left[-\dfrac{(F_{\text{inp}} - v_2^{\text{cen}})^2}{2(\sigma_2^{\text{sd}})^2}\right], \\ \dots, \\ \exp\left[-\dfrac{(F_{\text{inp}} - v_{\bar{g}}^{\text{cen}})^2}{2(\sigma_{\bar{g}}^{\text{sd}})^2}\right] \end{cases} \tag{7}$$

Here, $\left(F_{\text{inp}}, \bar{g}\right)$ indicate the input (i.e., $\left(G_{\text{avg}}, T_{\text{spe}}, F_{usg}\right)$ ) and the number of hesitant values, respectively, and $\left(v_{\bar{g}}^{cen}, \sigma_{\bar{g}}^{sd}\right)$ illustrate the center and standard deviation value of the membership function, correspondingly. Next, the inference data $\left(I_{fuz}\right)$ is obtained by combining ( $G_{avg}, T_{\text{spe}}, F_{usg}$ )with $R_{Fu}$. Finally, the crisp value ( $v_{\text{crip}}$ ) is obtained by performing defuzzification, providing the learning plateau detected outcome.

$$v_{\text{crip}} = \frac{\sum m_{GH}\left(I_{fuz}\right) \cdot v^{cen}}{\sum m_{GH}\left(I_{fuz}\right)} \tag{8}$$

Thus, the proposed GH-Fuzzy accurately detects the learning plateau by efficiently capturing non-linear performance variations and identifying stagnation patterns in students' learning progression. The plateau output $(v_{\text{crip}})$ is incorporated as a contextual input in hidden engagement analysis to distinguish whether performance stagnation arises from low engagement or learning difficulty. This ensures a coherent transition from plateau detection to learning behavior evaluation.

### 3.6. Hidden Engagement Pattern Analysis

Hidden engagement patterns capture implicit learner behaviours from interaction data, enabling differentiation between productive and passive learning to improve personalization in adaptive systems. Hidden engagement analysis using GH-Fuzzy differentiates productive and passive learning by evaluating time, usage, and performance metrics, classifying learners into engagement levels based on learning efficiency.

## 4. Result and discussion

Here, to prove the dependability of the proposed work, performance validation and comparative assessment are conducted. Also, the proposed model is implemented in the working platform of Python.

### 4.1. Dataset Description

The "College English Learning Dataset" is employed to train the feedback-driven adaptive English language learning model. This is a publicly available dataset, and the link is given in the reference section. The dataset, sourced from an online repository, captures real-time learner interactions, ensuring reliable evaluation of adaptive learning models. The dataset contains 500 instances with learner features, expanded to 3000 after augmentation, with 80% used for training and 20% for testing. This experimental setup ensures a balanced evaluation of the proposed model by validating its performance on unseen data and improving generalization capability.

### 4.2. Performance Validation

In this section, the performance validation is done for the proposed model and prevailing techniques regarding various performance metrics.

The proposed IQBiSLSTM, using efficient activation and sparse initialization, achieves superior classification performance, as shown in Fig. 2 and Table 1, with higher accuracy, PPV, sensitivity, and F-measure compared to conventional models.

### 4.3. Comparative Assessment

Here, the comparative assessment is done for the proposed and related works as follows,

Table 2 displays, the proposed CGSPQ-Learning and GH-Fuzzy model outperforms existing methods by improving decision-making while addressing limitations like low transparency, poor feedback quality, bias, and high computational cost.

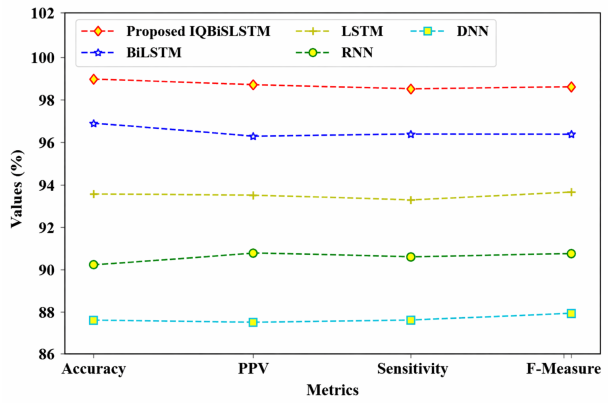


**Fig. 2.** Performance calculation regarding accuracy, PPV, sensitivity, and F-Measure

## 5. Conclusion

This paper presents a feedback-driven adaptive English learning model using CGSPQ-Learning and GH-Fuzzy, integrating preprocessing, augmentation, plateau detection, classification, and feedback analysis, achieving a rule generation time of 698 ms , classification accuracy of 98.8745%, PPV of 98.6325%, sensitivity of 98.4578%, MSE of 0.2145 , RMSE of 0.3265 , MAE of 0.3154 , and explanation fidelity of 0.9457 with stability of 0.9562 , demonstrating high reliability.

## 6. Practical implication

The proposed model supports real-time applications by improving workplace safety training, personalizing medical English learning, and enhancing legal English understanding through feedbackdriven analysis.

## 7. Future scope

Future work will incorporate multimodal signals such as eye gaze, facial expressions, and speech prosody to enhance hidden engagement modeling and improve adaptive learning accuracy.

## 8. Declaration

## 9. Data availability

Not applicable

## 10. Conflicts of interest

The authors declare that they have no known competing financial interests or personal relationships that could have

**Table 1.** Comparative evaluation for improvement classification

| Methods | Accuracy | PPV | Sensitivity | F-Measure |
|---|---|---|---|---|
| Proposed IQBiSLSTM | 98.8745 | 98.6325 | 98.4578 | 98.5236 |
| BiLSTM | 96.8475 | 96.2514 | 96.3289 | 96.3298 |
| LSTM | 93.5689 | 93.5247 | 93.2659 | 93.6528 |
| RNN | 90.1528 | 90.6359 | 90.4871 | 90.6327 |
| DNN | 87.5269 | 87.4578 | 87.5623 | 87.9529 |

**Table 2.** Comparative Evaluation

| Authors | Aim | Method | Merits | Demerits |
|---|---|---|---|---|
| Proposed Model | Feedback-driven adaptive English language learning model | CGSPQ-Learning and GH-Fuzzy | The model enhanced decision-making for improving student performance in English learning. | The proposed work did not consider multimodal engagement signals. |
| (Jia et al., 2022) [10] | Advanced learner system for English language learning | Artificial Intelligence (AI) | The model significantly improved the English learning process of L2 learners. | The model suffered from limited transparency and low user trust. |
| (Annamalai et al., 2023) [6] | English language learning for higher education | Push–Pull Mooring–Habit (PPMH) | The method demonstrated high effectiveness and robustness. | Feedback quality was inconsistent. |
| (Ma et al., 2025) [11] | AI-centric adaptive English language learning system | Recurrent Neural Network (RNN) | The model effectively supported non-native English learners. | The study exhibited proficiency-level bias. |

influenced the work reported in this paper.

## 11. Funding statement

This research received no external funding.

## 12. Author contribution

Based on an investigation of hidden engagement patterns, the author created the framework for feedback-driven adaptive English language acquisition. The Cgspq-learning and GH-fuzzy mechanisms were designed and implemented by the author, who also carried out the experimental research, analysed the findings, and wrote the original publication. The author evaluated and approved the manuscript' s final version.

## 13. Ethical approval

This article does not contain any studies involving human participants or animals performed by any of the authors.

## 14. Consent to participate

Not applicable.

## 15. Consent to publication

All authors have provided consent for publication of this manuscript.

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