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Design of an Adaptive English Vocabulary Learning System Based on Fuzzy Modeling of Second Language Vocabulary Features

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Abstract. Second language vocabulary acquisition is dynamic, individualized, and uncertain. Traditional vocabulary learning systems often use static difficulty grading or simple frequency statistics, which are difficult to accurately adapt to learners' cognitive states and real-time needs. In response to this issue, this article designs and implements an adaptive English vocabulary learning system based on fuzzy modeling of second language vocabulary features, using the cognitive psychology knowledge acquisition theory (three stages of understanding consolidation application) as the teaching framework. The system focuses on personalized vocabulary resource recommendation as its core goal, aiming to improve learning efficiency and stimulate learning interest. The overall architecture includes five functional modules: pre-test diagnosis, vocabulary acquisition, consolidation and application, effectiveness testing, and learning feedback, forming a closed-loop iterative learning path. At the algorithmic level, the system introduces fuzzy logic as the main inference mechanism, breaking through the rigid discrimination of "right or wrong" in classical binary logic, and using multi value membership degrees to describe the continuous spectrum of learners' abilities. In the fuzzification stage, four behavioral indicators are selected as input variables: daily online learning duration, daily vocabulary growth, average answering time, and total vocabulary mastery. The data is obtained from real-time records in the database, and the current vocabulary mastery level and cognitive load level of learners are inferred through the fuzzy rule library. The difficulty, frequency, and presentation of recommended content are dynamically adjusted. Preliminary applications have shown that the system can adaptively optimize learning paths based on individual behavior patterns, and has significant advantages in promoting long-term vocabulary retention and enhancing autonomous learning motivation, providing a feasible technical solution for personalized second language vocabulary learning.

Keywords: fuzzy logic, adaptive learning, second language vocabulary acquisition, personalized recommendation

1 Introduction

In the process of human language learning, it is generally divided into first language and second language. The first language refers to the language that humans first learn and acquire, that is, the mother tongue, and the second language generally refers to any newly added language learned after the mother tongue. This classification method usually distinguishes based on the order of learning, only looking at the order, without distinguishing social environment. As the main second language in China, learning English vocabulary has always been a top priority in English learning. Therefore, how to use scientific and effective methods and unique techniques to help learners quickly master and memorize English vocabulary has become a hot research area for current researchers.

There are numerous learning materials related to English vocabulary learning, and the overwhelming amount of materials has led to a flood of English learning resources. How English learners can find scientific and suitable learning methods among the numerous learning materials is a major concern for them. English vocabulary learning materials can be divided into two types in terms of resource format: paper materials and

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electronic materials [1]. Paper materials are generally promoted and published by well-known English learning institutions, such as Spark English Vocabulary, New Oriental English Vocabulary, Foreign Language Teaching and Research Press English Vocabulary, Victor English Vocabulary, etc; Electronic materials are mainly used for online learning, and the main forms of online learning are websites and mobile apps. Typical online learning websites or mobile apps include BBC Learning English and British Council, which are well-known English resource websites, while "BaiCiZhan", "MaiMemo-Recite Words", and "Shanbay Word" are typical mobile apps. The resources of online English learning websites are relatively well allocated within the framework of English learning, and each has its own advantages and characteristics, which to some extent facilitates learners to make reasonable choices when using resources. However, when viewing existing online and offline resources, each specific learning framework lacks differentiated classification for specific learning groups, and there is no detailed division of learning content based on learners' own learning characteristics. Therefore, it is difficult for learners to achieve higher learning outcomes. Conventional English vocabulary learning apps often occupy over 70% of the page layout in terms of images and videos, while the analysis and description of words themselves only occupy a small corner with a dull color tone. For teenagers who lack a firm learning will or persistent learning enthusiasm, more attention will be paid to images and videos, seriously affecting learning efficiency and effectiveness. At the same time, most English vocabulary learning apps lack practical auxiliary tools for practical use. Although it can help learners' memory from the perspective of scenario creation, the root cause ignores the initial and ultimate goals of learning, and the negative effects it brings will far outweigh the positive effects it provides [2].

At present, most research on English vocabulary learning methods and how to improve learning efficiency is still in the theoretical stage, and it is impossible to combine existing theories with existing online English learning resources. The development of some learning systems mainly focuses on the accumulation of vocabulary and the repeated consolidation of vocabulary, but neglects the application of vocabulary. Therefore, through the analysis of the above content, how to enable English learners to obtain learning resources that are suitable for their own learning characteristics and reasonable planning of the learning process is the research direction of this article. We will refer to this learning method that specifies specific learning resources and frameworks for each learner as adaptive learning method. By combining this method with online learning resources, we can enable learners to learn English vocabulary effectively. Fully experiencing learning. The process of acquiring, consolidating, and applying to achieve efficient English learning [3].

2 Related Work

There are many research results worth learning from on how to improve learners' recommendation of learning content and English vocabulary. Adaptive learning has already appeared in the learning of knowledge content in other fields, and this article mainly targets the population whose mother tongue is Chinese and whose second language is English. Rehan S. Ali, A self-adaptive learning system for business English learning has been designed, which automatically recommends learning content that is suitable for learners' learning difficulty and learning field based on their learning performance, knowledge level, and emotional feedback. Finally, through experiments comparing the learning performance of the control group, it has been proven that the system can improve learners' learning performance [4].

Nianfan Peng, Propose a method for testing English vocabulary learning outcomes, which is based on neural networks and artificial intelligence technology. Construct a machine learning based computer English learning performance evaluation model, and use the model to evaluate English learning performance. This method has reference significance for the design of the "learning situation statistics module" in this article's system [5].

Anastasiya Rybakova, A multimodal robot assisted learning framework was studied, featuring OpenManipulator-X, and an interactive robot system was designed to support English learning for Korean preschool children. The framework has interactive and learning behavior statistical functions. Finally, comparative experiments were conducted to demonstrate that the adaptive learning method can effectively improve learners' efficiency in learning English vocabulary [6].

Zunlan Xiao, the author constructed an English education resource network, which can significantly improve the accuracy and personalized learning resources recommended by learners on online education platforms. The main contribution of the article is the successful construction of an English education resource network using knowledge graphs, which can deeply analyze user behavior data and course content, and propose an adaptive recommendation algorithm (ARA) to provide users with customized learning resources. Meanwhile, in terms of

data collection and processing, we have integrated over 100000 pieces of user learning behavior data, including their learning history, preferences, and resource interactions, providing ideas for the design of the "feature analysis module" in this article [7].

Rui Wang, in response to the current situation of feedback delay, subjectivity, lack of personalization, technical limitations, and lack of long-term analysis in traditional English speech training feedback mechanisms, the SVM model is used to accurately recognize English phonemes or words, thereby enabling real-time evaluation of students' learning situation. Then, the reinforcement learning mechanism is used for real-time evaluation and personalized adjustment of learners' learning plans, providing instant feedback and dynamic training plans. The integration of the two models forms a multidimensional feedback system for evaluating pronunciation performance, and continuous improvement suggestions are provided through long-term data analysis. Finally, the Q-learning model reinforcement learning system maintains a high reward mean and significantly improves training effectiveness [8].

Based on the above research orientation, the structure of this article is as follows: Section 1 describes the background and significance of the system developed in this article, Section 2 mainly searches for relevant research results, aiming to provide improvement solutions for the system design of this article by drawing on existing research results, Section 3 introduces the design framework and main design process of this system, describes the design schemes of each functional module, Section 4 describes the adaptive fuzzy recommendation method, provides the fuzzy reasoning model and fuzzy reasoning rules, Section 5 is the experimental and simulation stage, and the simulation and experiments of this article mainly verify the feasibility of the proposed method.

3 Design and Implementation of Adaptive Learning System Framework

3.1 System Function Design

In the design process of the adaptive learning system framework, the research results of cognitive psychology in knowledge learning and acquisition are taken as the main framework. The framework includes three links: knowledge understanding, knowledge consolidation, and knowledge application. These three links are used as the guiding ideology for system construction, and the main purpose is to achieve personalized vocabulary resource recommendation for learners [9]. The entire system is designed and developed with the main goal of helping learners improve learning efficiency and cultivate learning interest. The functional modules are mainly divided into five main parts: feature analysis module, vocabulary learning and understanding module, reinforcement and application module, simulated exam module, and learning situation statistics module. Fig. 1 presents the functional architecture of the entire system [10].

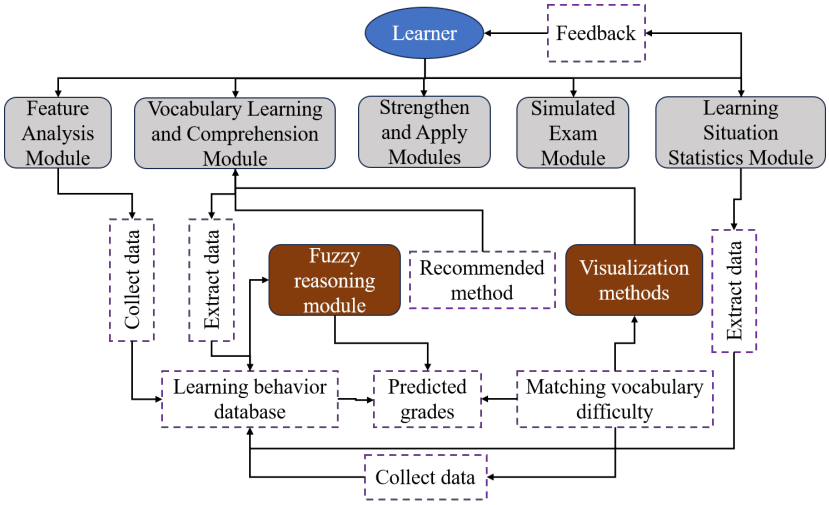


Fig. 1. System architecture diagram

1) Feature Analysis Module. The feature analysis module is the initialization module for learners to use the learning system, with the purpose of collecting learners' raw data. The learners' raw data includes their current cognitive level, vocabulary mastery, learning ability, etc. The highlight of the feature analysis module is the analysis of learners' learning habits. However, for new users, the database does not have relevant information about new users. Therefore, in order to accurately evaluate learners' learning foundation level and prepare for personalized vocabulary recommendations in the future, this system needs to complete initial practice tests and assessments when learners first use it, collect effective information on learners' average problem-solving time, accuracy, grade scores, etc. as initial data, and store it in the learning behavior database [11].

2) Vocabulary Learning and Comprehension Module. The vocabulary learning and understanding module is the core part of the system, which mainly helps learners to complete the learning of English vocabulary and deepen their understanding. Based on the data obtained from the feature analysis module, this module uses a fuzzy inference model to perform its main functions. The system will first collect four basic information about learners' daily learning time, daily vocabulary growth, total vocabulary mastery, and average problem-solving time from the behavior database. After a fuzzy reasoning process, it will obtain an estimated test score for learners' current cognitive level. Then, based on the score, it will match words with similar difficulty coefficients from the English vocabulary database as learning resources for recommendation. This functional module also provides a variety of vocabulary memory methods to meet the different learning styles of learners. The design style of the vocabulary learning interface of the system is not a real learning interface. The interface focuses on the words themselves and reduces excessive interference from images, videos, etc. Learners can use the memory method of the vocabulary itself to present the words themselves and their Chinese explanations on the interface. In order to avoid the fatigue of rote learning, the system provides corresponding pictures to help learners construct corresponding learning situations and assist in memory. The envisioned interface also includes the following functions: by displaying other words related to memorizing vocabulary, such as synonyms, antonyms, gerunds, past participles, etc., it helps learners establish a vocabulary system structure and strengthen memory. In addition to the application of various memory methods, this module also provides the functions of difficult word record book and proficient word removal. Learners can add their own difficult vocabulary to the difficult word record book for key annotation, practice repeatedly, and also remove the mature vocabulary to ensure that the system no longer recommends it, saving learning time. But once the learner makes a mistake in using the removed proficient vocabulary during the test, the system will automatically reintroduce the removed words into the new vocabulary and recommend them again. Due to the daily changes in learners' vocabulary, their cognitive level of vocabulary is also changing. Vocabulary is recommended based on learners' current level on the day, and each login will re evaluate learners' learning ability and match vocabulary with corresponding difficulty levels. The recommended vocabulary for the day that has been mastered should be marked and no longer recommended. The vocabulary that has not been mastered should be integrated into the vocabulary library and re recommended, repeating the process until the learner has mastered the vocabulary [12]. The functional interface of the vocabulary learning and understanding module is shown in Fig. 2.

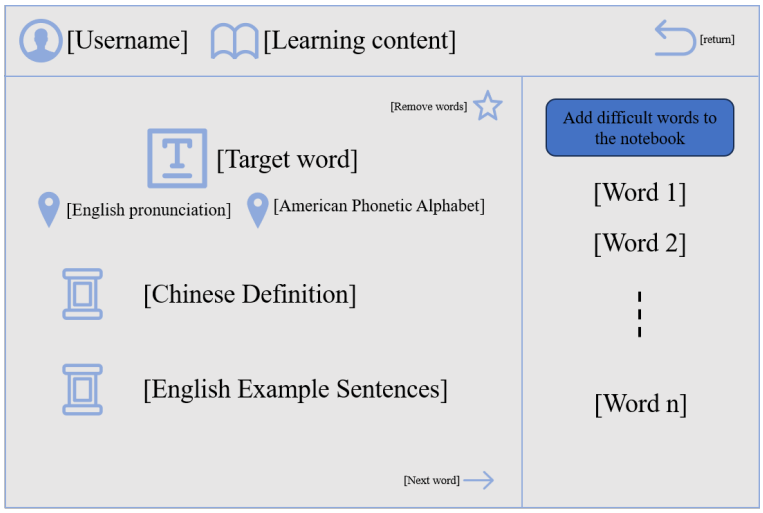


Fig. 2. Vocabulary interface

3) Strengthen and Apply Modules. The reinforcement application module corresponds to the reinforcement and scenario application stages of the learned words, helping learners review and enhance learning effectiveness. In terms of word reinforcement, the system supports summarizing and categorizing daily recommended vocabulary. Words that have been proficiently removed are marked in green font, while words added to the difficult word record book are marked in orange font. Considering the situation of memory forgetting, learners can search for "removed" vocabulary records in the exclusion records for easier review and consolidation. In terms of knowledge application, the system will incorporate the vocabulary that appears on the day into common phrases or sentences to help learners deepen their impression and achieve the process of knowledge transfer through practical use. This module also includes a daily quiz feature to track learners' question time and provide them with learning feedback. Incorrect vocabulary will be automatically included in new vocabulary recommendations [13]. The design scheme for the reinforcement and application module is shown in Fig. 3.

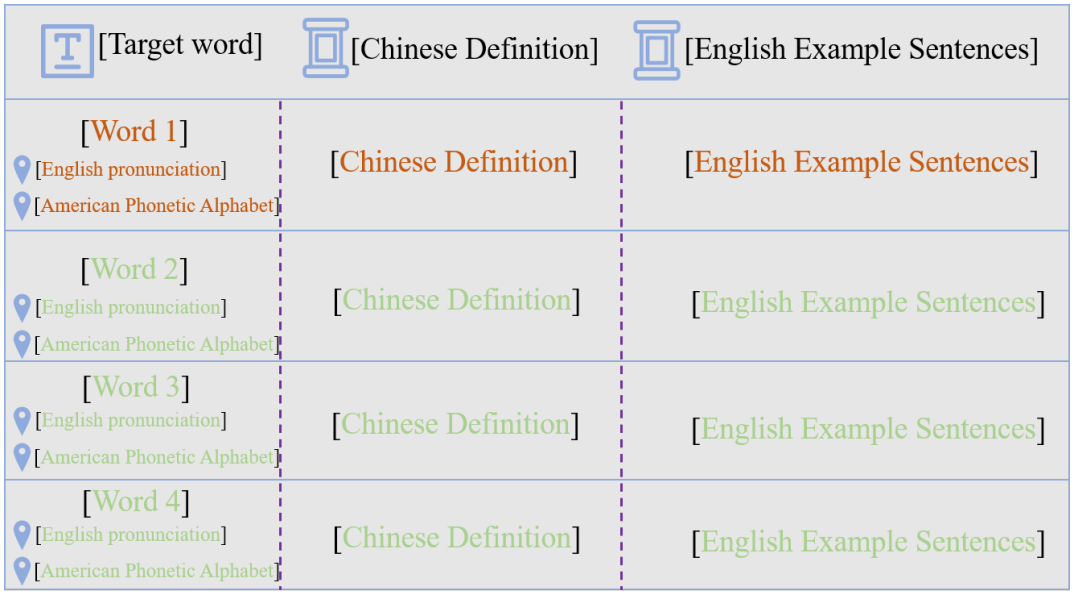


Fig. 3. Recommended vocabulary interface

4) Simulated Exam Module. The purpose of setting up the simulated exam module is to collect learners' learning characteristic information, and recommend vocabulary to learners through fuzzy reasoning. Taking high school students learning English vocabulary as an example, the simulated exam module randomly selects all 3500 vocabulary words from high school, and with the same test difficulty standard, the trend of learners' vocabulary mastery can be clearly observed. If the learner's accuracy rate in each simulated exam is around 96%, it indicates that the learner has basically mastered all the vocabulary content of the college entrance examination, and has reached the system's practical value. The mock exam is conducted in a 7-day cycle, with relatively simple content and clear objectives, focusing on the vocabulary itself, examining learners' pronunciation, spelling, and Chinese English translation meanings, and reviewing learners' memory level of vocabulary [14].

5) Learning Situation Statistics Module. The learning situation statistics module can provide learners with feedback on their learning information. Providing feedback on learning outcomes to learners can help them reflect and improve. Firstly, in terms of learning motivation, informing learners of the correctness and errors of learning methods can lead to emotional experiences of satisfaction or dissatisfaction, further affecting their motivation to learn; In terms of cognition, learners can use the obtained learning outcomes as directional guidance for future learning. Studies have shown that learners who understand learning outcomes have higher learning motivation, faster progress, and significant learning effects than those who do not. In addition, the timeliness of learning feedback is also an important factor affecting learning outcomes. Continuous feedback can play a better role than intermittent feedback. Based on the above theory, the learning situation statistics module of the system will update the learning situation of learners in a timely manner, and the data will be re read every time the interface is refreshed. As shown in Fig. 4, learners can obtain feedback data from their personal center.

Mainly using data visualization methods such as line charts and sector charts, personal feedback information such as the percentage of vocabulary mastered among all vocabulary, trends in test scores, ranking of personal vocabulary memory among all system users, average daily learning time, and daily vocabulary growth are displayed [15]. The final statistical results of the learning situation statistics module are shown in Fig. 4.

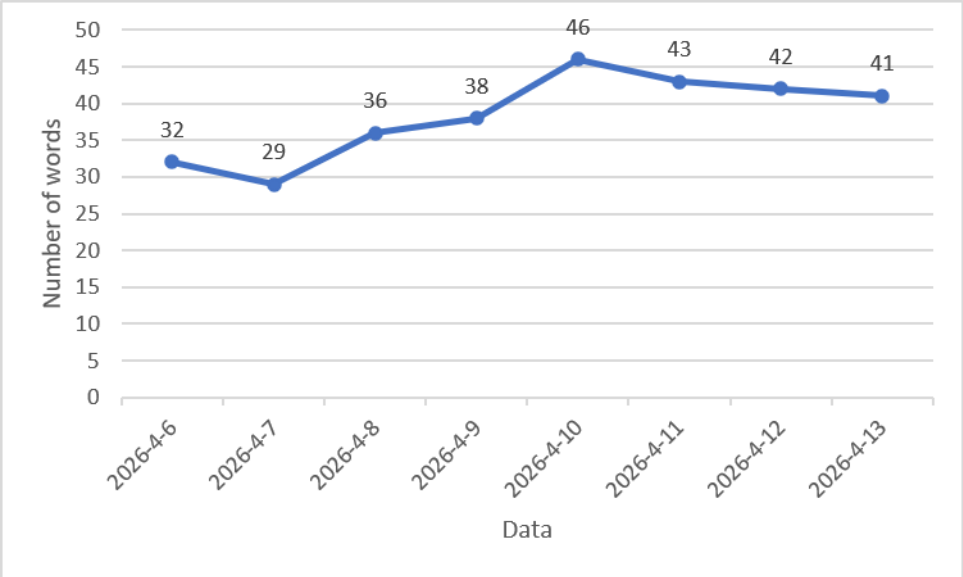


Fig. 4. Visualize data lines

3.2 Function Implementation and Code Design

The system adheres to the development principles of simplicity, usability, security, reliability, and open reuse, separating the server from the web front-end to improve development efficiency and ensure smooth system usage. The server uses exposed interfaces and JSON data format for transmission, which can be accessed and called by the front-end for interface display [16]. The overall architecture and hierarchical diagram of the system are shown in Fig. 5.

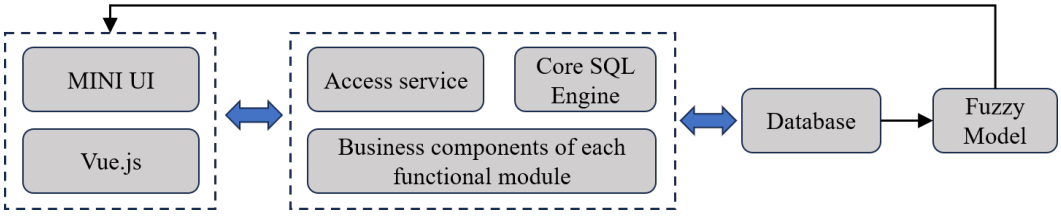


Fig. 5. Overall architecture and hierarchical diagram of the system

In terms of the overall architecture of the system, SublimeText3 is mainly used for the front-end, while Eclipse is used as the development tool for the back-end. For the selection of web containers, Tomcat is not used for convenience, speed, and ease of use, but a more lightweight Jetty is adopted. The application layer provides standard HTTP service interfaces, supports session state, and enables integration with web terminals. The business service layer implements the main functions of the system, including pre use testing, vocabulary recommendation, personal information feedback, and evaluation testing. For data persistence operations, the system adopts MySQL database, which is known for its small size, fast speed, and low overall cost of ownership.

For the front-end development part, in order to accelerate the development progress, front-end frameworks such as JQuery, MINIUI, Vue.js were adopted. JQuery is a fast and concise JavaScript framework that facilitates the retrieval of page elements, greatly simplifying complex and diverse JavaScript code. MINI UI is a rapid web interface development framework. It can shorten development time, reduce code volume, enable developers to focus more on business and server, and easily achieve interface development. Using MiniUI, developers can quickly create Ajax without refresh, B/S for quick data entry CRUD, Master-Detail, Typical web application system interfaces such as menu toolbar, pop-up panel, layout navigation, data validation, pagination table, tree, and tree table. Vue.js is a lightweight, high-performance, component-based front-end data-driven framework. The core library of Vue focuses only on the view level and is also easy to learn and integrate with third-party libraries or existing projects. The backend development part is mainly developed using Java language. In terms of database persistence, MyBatis core SQL engine is mainly used. MyBatis is an excellent database persistence framework developed in Java that supports regular SQL queries, stored procedures, and advanced mapping. It can automatically map data to Java objects, making it easier and faster for system developers to access database data, greatly saving development time and maintenance costs [17].

The harmony of vocabulary refers to whether the pronunciation and spelling of words are consistent. Vocabulary with high harmony can be memorized in alphabetical order based on their pronunciation, reducing the difficulty of vocabulary memorization. On the other hand, vocabulary with relatively low harmony will have at least one unvoiced letter, which will increase the difficulty of memorization. By comparing various high school English vocabulary difficulty classification systems, the high school English curriculum standard vocabulary list was ultimately selected as the reference standard for the vocabulary level classification system in this research system. The vocabulary list includes about 3500 high school English words, which are classified into five levels based on their frequency of use: 1, 2, 3, 4, and 5. The frequency of vocabulary words from level 1 to level 4 decreases gradually, and the difficulty coefficient decreases step by step, increasing the difficulty. However, the words marked with an asterisk are some out of class vocabulary, with the lowest difficulty coefficient and the highest difficulty.

The main deduction algorithm of this system, fuzzy logic, requires four variables in the fuzzification stage: daily average online learning time, daily average vocabulary growth, average answering time, and total vocabulary mastery, which need to be obtained from the database records. The core query statements are as follows:

```
-- Set parameters
SET @user_id = 'target_user_id';
SET @end_date = '2026-07-20';        -- analysis date
SET @window_days = 30;               -- retrospective window for daily averages
SET @start_date = DATE_SUB(@end_date, INTERVAL @window_days DAY);
-- Main query: returns all four variables in one row
SELECT
    -- Variable 1: Average daily online study duration (minutes)
    COALESCE(
        (SUM(TIMESTAMPDIFF(MINUTE, start_time, end_time)) / @window_days),
        0
    ) AS avg_daily_duration,
    -- Variable 2: Average daily vocabulary growth (newly mastered words per day)
    COALESCE(
        (COUNT(DISTINCT CASE
            WHEN mastered_date BETWEEN @start_date AND @end_date
            THEN word_id
        END) / @window_days),
        0
    ) AS avg_daily_growth,
    -- Variable 3: Average response time per question (seconds) within the window
    COALESCE(
        AVG(CASE
            WHEN attempt_date BETWEEN @start_date AND @end_date
            THEN response_seconds
        END),
        0
    ) AS avg_response_time,
    -- Variable 4: Total vocabulary mastered up to the analysis date (cumulative)
```

```
    COALESCE(
        COUNT(DISTINCT CASE
            WHEN mastery_status = 'mastered'
            AND mastered_date <= @end_date
            THEN word_id
        END),
        0
    ) AS total_mastered
FROM
    -- Dummy left-join to ensure zero results if some tables have no records
    (SELECT 1) AS dummy
LEFT JOIN
    study_records sr ON sr.user_id = @user_id
    AND sr.end_time BETWEEN @start_date AND @end_date
LEFT JOIN
    word_attempts wa ON wa.user_id = @user_id
    AND wa.attempt_date BETWEEN @start_date AND @end_date
LEFT JOIN
    user_vocabulary uv ON uv.user_id = @user_id
    AND uv.mastered_date <= @end_date;
```

The code for calculating the estimated grades of students based on the data queried in the database by the backend is as follows:

```
public double getScore(int testTime[], int studyTime[], int totalNum[], int add-
Num[]) throws Exception{

               double score = 0;
for(int i = 0; i < testTime.length; i++){
for(int j = 0; j < studyTime.length; j++){
for(int k = 0; k < totalNum.length; k++){
for(int l = 0; l < addNum.length; l++){
int singleScore = 0;
DataRow datarow = dao.findWeightByLevel(testTime[i], studyTime[j], totalNum[k],
addNum[l]);
if(datarow.msgCode == 0){
switch(datarow.scoreLevel){
case ScoreLevel.one:
singleScore = 20 * datarow.weight;
break;
case ScoreLevel.two:
singleScore = 40 * datarow.weight;
break;
case ScoreLevel.three: singleScore = 60 * datarow.weight;
break;
case ScoreLevel.four: singleScore = 80 * datarow.weight;
break;
case ScoreLevel.five: singleScore = 100 * datarow.weight;
break; }
score += singleScore; }else{ throw new BussinessException(); } } } } } return
score; }
```

The recommendation of vocabulary is once a day and only recommends vocabulary that learners have not yet mastered. Daily random recommendations, up to a maximum of 100. The query statement for obtaining recommended vocabulary is as follows:

```
FUNCTION defuzzify(activations Map) RETURNS Float {
    numerator = 0.0;
    denominator = 0.0;
    // Weighted Average (Centroid) method using singleton centroids
```

```
    FOR EACH (set_name, activation_level) IN activations {
        // Skip sets with zero activation to avoid adding zero weights
        IF activation_level > 0 THEN
            centroid = OUTPUT_SETS[set_name];   // get the representative score
            numerator = numerator + (activation_level * centroid);
            denominator = denominator + activation_level;
        END IF;
    }
    // If denominator is zero (no rules fired), return a default middle score
    IF denominator == 0 THEN
        RETURN 50.0;    // Neutral score
    END IF;
    // Normalize to get final crisp score (0~100)
    predicted_score = numerator / denominator;
    // Clamp the result to [0, 100] to avoid floating point overflows
    predicted_score = MAX(0.0, MIN(100.0, predicted_score));
    RETURN predicted_score;
}
FUNCTION predict_student_score(user_id VARCHAR) RETURNS JSON {
    // Step A: Fetch crisp learning features from database
    features = get_learning_features(user_id);
    // Step B: Fuzzification - Convert each crisp value to fuzzy sets
    fuzzy_duration  = fuzzify_duration(features.avg_duration);
    fuzzy_growth    = fuzzify_growth(features.avg_growth);
    fuzzy_response  = fuzzify_response(features.avg_response);
    fuzzy_total     = fuzzify_total(features.total_mastered);
    // Package all fuzzy inputs into a single map for rule evaluation
    fuzzy_inputs = {
        'duration': fuzzy_duration,
        'growth':   fuzzy_growth,
        'response': fuzzy_response,
        'total':    fuzzy_total
    };
    // Step C: Inference - Apply fuzzy rules to get output activations
    rule_activations = evaluate_rules(fuzzy_inputs);
    // Step D: Defuzzification - Compute the final crisp predicted score
    final_score = defuzzify(rule_activations);
    // Step E: Return result (log raw data for debugging/tuning)
    RETURN {
        'status': 'success',
        'user_id': user_id,
        'predicted_score': ROUND(final_score, 2),
        'fuzzified_inputs': fuzzy_inputs,      // optional for monitoring
        'rule_activations': rule_activations   // optional for monitoring
    };
}
```

The backend packages all the queried vocabulary information into parameters, and the frontend retrieves the data through interface calls and presents it to learners using visual techniques.

4 Establishment of Fuzzy Model

Fuzzy logic proposes a multi value theory viewpoint on the intermediate zone between binary values, which is based on the classical theory of non-zero equals one and non yes equals no. The idea of fuzzy logic can be used to process information with uncertainty, record people's complex and changing behavior patterns, and predict various possible scenarios.

Let any set S, any element a in the domain of discourse, belong to set S or not, and thus the characteristic function of set S can be defined as:

$$F(a)=\begin{cases}1, a \in S\\ 0, a \notin S\end{cases} \tag{1}$$

However, for fuzzy sets, elements in the domain can partially belong to set S. Here, the concept of membership degree is introduced to represent the degree to which an element belongs to set S. Fuzzy sets can be defined using membership functions. Assuming there exists a fuzzy subset of set $S_{general}$ that can be determined by any mapping of ordinary sets $S_{general}$ and $S_{general}$ on interval [0,1], it is called the fuzzy set S on $S_{general}$. Among them, mapping m is the membership function of the fuzzy set, and for any element $S_{general}$ in set $S_{general}$, $m(S_{general})$ is the membership degree of $S_{general}$ to the fuzzy set. The higher the value of $m(S_{general})$, the higher the degree to which element $S_{general}$ tends towards set S, and vice versa, the lower the degree to which $S_{general}$ tends towards S. The fuzzy set S can be represented as:

$$S=\left\{\left(s_{general}, F\left(s_{general}\right)\right)\middle| s_{general} \in S_{general}\right\} \tag{2}$$

The degree to which an element belongs to a fuzzy set is expressed as:

$$d(f)=\frac{1}{1+\left(\frac{f-c}{w}\right)^{2s}} \tag{3}$$

In the formula, f represents the frequency of learners accessing the learning content, c and w are used to adjust the center and width of the membership function, and s reflects the slope of the intersection point.

Fuzzy logic belongs to a type of multi valued logic, in which the values of variables may appear at any position within the interval [0,1]. Therefore, the operation rules for fuzzy sets can be summarized as taking the intersection as small, the union as large, and the complement as remainder [18]. Using X and Y as two variables, they can be expressed as the intersection:

$$X \cap Y=\min(X, Y) \tag{4}$$

The union is represented as:

$$X \cup Y=\max(X, Y) \tag{5}$$

Complementary representation is:

$$\begin{cases}\overline{X}=1-X\\ \overline{Y}=1-Y\end{cases} \tag{6}$$

After clarifying the basic concepts of fuzzy sets and membership degrees, we now delve into the process of fuzzy reasoning. The process of fuzzy reasoning is the calculation process of inputting a series of fuzzy sets, combining them with a fuzzy rule library to perform inference operations, processing, and outputting specific fuzzy result sets. In short, this is a process from multiple uncertain sets of conditions to an imprecise set of results, which is the core idea and key operating mechanism of fuzzy logic theory. Fuzzy rules are the criteria and standards followed by fuzzy reasoning, which can generally be expressed in natural language [19]. The expression for this rule is:

$$\begin{array}{llll} if & a & is & S\\ then & b & is & B\end{array} \tag{7}$$

Among them, a is the variable name in the rule, S is the specific value in a fuzzy set with a domain $S_{general}$, b is the result name, and B is the specific value in the result set with a required domain W. If Little A has long legs, then Little A runs very fast; if Little B is fat, then Little B exercises less; if Little C is strong, then Little C has more strength, and so on. Of course, when facing specific situations in life, variables are mostly not a single one, but a collection of multiple attributes, and fuzzy rules are usually a set of empirical rules expressed in natural language. Considering and analyzing from multiple dimensions, based on a scientifically reasonable rule system, is also beneficial for deducing results more accurately [20].

The process of fuzzy reasoning generally consists of five stages: determining input items, fuzzifying, reasoning, deblurring, and outputting. Some scholars have also combined the input term with fuzzification in one step, forming four main steps, which are essentially similar to what is discussed in this article. The first step in fuzzy reasoning is to establish the input items. The establishment of input items has a significant impact on the accuracy of the output results. Generally speaking, the more dimensions considered and the more detailed the analysis of the attributes of the research object, the higher the accuracy and credibility of the results obtained [21]. The operation of the fuzzification process is to convert the input items into the input values set by the program after corresponding processing. That is to say, the process of obtaining the membership degree of a fuzzy set from specific inputs based on the membership function. This process completes the transformation of fuzzy inference input values into corresponding fuzzy linguistic variables, in other words, it achieves the mapping of input values to fuzzy sets in the domain of fuzzy linguistic variables, providing a method for data transformation. The reasoning stage is the core stage of the entire process and also the essence of the fuzzy reasoning mechanism. This kind of reasoning is not precise reasoning, but an approximate reasoning that achieves the process of deriving an imprecise conclusion from the processing, deduction, and operation of an uncertain set. In this stage, the corresponding fuzzy conclusions are obtained by calculating the membership degrees of the fuzzy rules and the relevant fuzzy sets of the input. The fuzzy rule library is the key to the survival of the entire reasoning process, serving as the standard and rules for reasoning. It to some extent determines the correctness and accuracy of the final result, so the selection of fuzzy rules determines the development direction of the entire fuzzy reasoning process. It is a control rule derived by relevant experts through the analysis of a large amount of data and combined with relevant knowledge and experience, specifically applicable to the control of specific natural language expression variables. In the deblurring stage, the fuzzy conclusions obtained in the inference stage are transformed according to a certain calculation method to obtain a specific clear quantity, and then scaled according to the corresponding requirements in practical applications, ultimately obtaining the precise answer required in practical applications [22]. In short, the process of deblurring is to transform fuzzy conclusions into concrete and accurate output processes. The relationship between each stage is shown in Fig. 6.

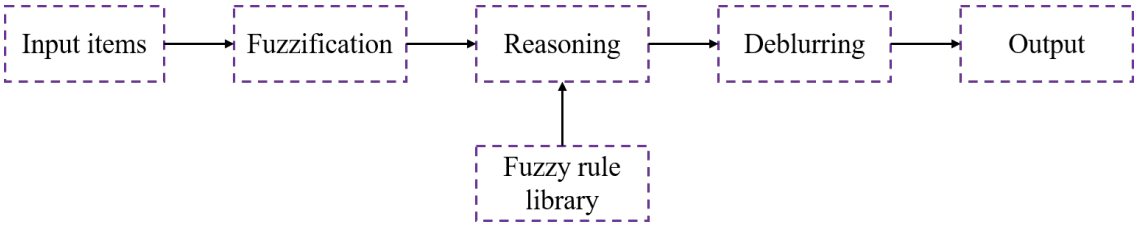


Fig. 6. Schematic diagram of the relationship between each stage

According to the reasoning formula of the rule, for the fuzzy set S and the fuzzy set S', the reasoning process is expressed as:

$$S' = (B) o (B \times S) \tag{8}$$

The process adopts Mamdani inference, and the deblurring process of the inference results uses the centroid method to find the center of the fuzzy set. The solving process is as follows:

$$\hat{O} = \frac{\int \left(d_B \left(\hat{O}_A \right) \bullet O_A \right) dO_A}{\int d_B \left(\hat{O} \right) dO_A} \tag{9}$$

This article adopts fuzzy control rules, which have a guiding effect on the entire experimental research. At the same time, fuzzy control rules also determine the scientificity and accuracy of the research results. The establishment of rules often relies on extensive data analysis and mining to identify commonalities between data, discard differences between data, and encompass all possibilities of data [23].

The adaptive fuzzy inference process of the system is shown in Fig. 7.

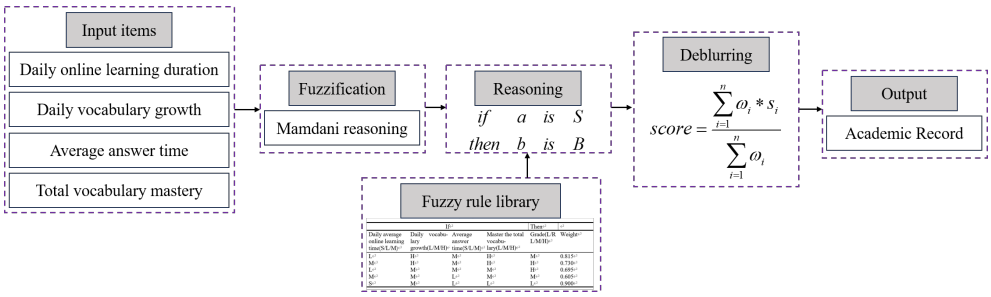


Fig. 7. Adaptive fuzzy inference process of the system

In the process of using the system, each learner corresponds to a specific fuzzy control rule as an element that constitutes the overall fuzzy rule. For example, if learner A has a long daily learning duration (DLD), a high daily vocabulary growth (HDV), a short average answering time (SAAT), and a high master of vocabulary (HMV), then their score is good (G). This can be described in fuzzy language as if their daily online learning duration is long, their daily vocabulary growth is high, their average answering time is short, and their total vocabulary is high.

Due to the "and" relationship between the input quantities, an intersection relationship is adopted for the comprehensive consideration of various dimensions, and the minimum value (min) is taken to represent the weight of the rule. Therefore, the weight of the *i*-th rule generated by the *i*-th learner can be expressed as:

$$\omega_i = \mu_{dti} \cap \mu_{dni} \cap \mu_{ati} \cap \mu_{tni} \tag{10}$$

The processing of data in the deblurring stage is to convert a series of parameter variables obtained in the inference stage into a clear quantity as the output result. The process of deblurring in an adaptive English vocabulary recommendation system is to convert four input quantities: long daily online learning time, daily vocabulary growth, average answer time, and total vocabulary mastery, into estimated student grades, and this grade score is the required output quantity. Based on the weights of each rule obtained in the fuzzy reasoning stage and the total score of the mapping, the learner's estimated score can be expressed as:

$$score = \frac{\sum_{i=1}^{n} \omega_i * s_i}{\sum_{i=1}^{n} \omega_i} \tag{11}$$

Based on the three regions of the daily online learning time variable, the four regions of the daily vocabulary growth variable, the three regions of the average answer time variable, and the four regions of the total vocabulary mastered by learners, for rules with the same conditions (if the four attribute dimensions of the conditions are the same), the one with the highest weight is selected for retention, and the rest is discarded. The results of obtaining a portion of the effective rules are shown in Table 1.

Table 1. Fuzzy control rule table

If				Then	
Daily average online learning time (S/L/M)	Daily vocabulary growth (L/M/H)	Average answer time (S/L/M)	Master the total vocabulary (L/M/H)	Grade (L/RL/M/H)	Weight
L	H	M	H	M	0.815
M	H	M	H	H	0.730
L	M	M	M	H	0.695
M	M	L	M	M	0.605
S	M	L	L	L	0.900

The processing of data in the deblurring stage is to convert a series of parameter variables obtained in the inference stage into a clear quantity as the output result. The process of deblurring in an adaptive English vocabulary recommendation system is to convert four input quantities: long daily online learning time, daily vocabulary growth, average answer time, and total vocabulary mastery, into estimated student grades, and this grade score is the required output quantity. The maximum score for simulation testing in the system is 100 points. In order to obtain more accurate output results, the scores should be segmented and modularized as much as possible. The partitioning rules can be divided using the partitioning method shown in Table 2.

Table 2. Score partitioning rules

Excellent	Good	Generally	Not passing
90-100	80-89	60-79	Below 60 points

Finally, based on the level of the score, search for the corresponding difficulty level vocabulary in the vocabulary library and push it to the learner. Of course, in order to meet the dynamically changing vocabulary abilities of learners, they will be reevaluated every day when logging into the system to ensure the rationality of resource push.

5 Experimental Results and Simulation

The test scores can best reflect the students' vocabulary mastery status. As the test questions in this system's testing module are aimed at all the required vocabulary in the college entrance examination syllabus, the difficulty level of the questions remains consistent. Therefore, the results of the pre-test and post test can well reflect the changes in learners' mastery level. In terms of average scores, the experimental subjects were divided into two groups based on their pre-test scores, with the pre-test control group scoring 52 points, the highest score being 82 points, and the lowest score being 24 points. The experimental group scored 54 points, the highest score being 84 points, and the lowest score being 20 points. The post test results showed that the control group had an average score of 68 points, with the highest score of 92 points and the lowest score of 38 points. The experimental group had an average score of 74 points, with the highest score of 94 points and the lowest score of 52 points. The comparison results are shown in Fig. 8.

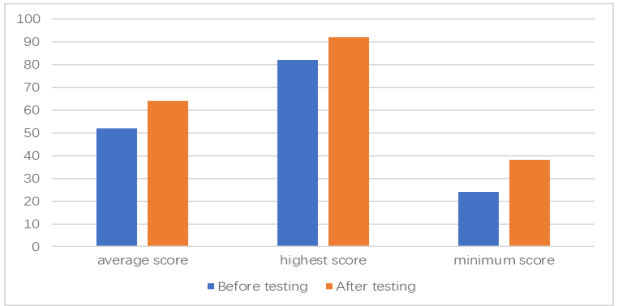


Fig. 8. Comparison experiment results

From the above data, it can be preliminarily concluded that after one month of learning, both the experimental group and the control group have made relatively significant improvements in their grades. This indicates that the students' learning status is relatively good, and they have invested a lot of energy in vocabulary memory. The students' wholehearted dedication also ensures the reliability and accuracy of the experimental results. However, in terms of the magnitude of the average score improvement, the experimental group was slightly higher than the control group, indicating that using an adaptive vocabulary learning system can help learners' vocabulary memory to some extent. Through in-depth observation, it was found that the changes in the highest scores of the pre-test and post test groups were roughly the same, while the experimental group showed a significant increase in the lowest score compared to the control group. In response to this situation, analyze the variance of the scores of the two groups again.

Learners' evaluation of the system is one of the effective ways to test its effectiveness. This article designs and distributes a questionnaire, collects questionnaire data information, analyzes learners' emotional attitudes towards the system usage experience, draws conclusions, and serves as the basis for system improvement and perfection. The survey results of the questionnaire are shown in Table 3.

Table 3. Survey questionnaire results

	Agree	General	Disagree
1. For vocabulary learning, it is necessary for the system to recommend resources.	4 (16%)	16	2
2. The use of the system has improved your grades.	18 (72%)	5	3
3. Learning the vocabulary recommended by the system is not too difficult.	20 (80%)		
4. The system information is presented clearly, easy to understand, and the learning process is visible, which helps to understand the learning status.	19 (76%)	4	4
5. Auxiliary functions such as vocabulary images, pronunciation, and related vocabulary listing are beneficial for increasing imagination space.	13 (52%)		
6. The presentation of system charts provides good feedback on the trend of learning status changes, such as daily vocabulary growth, mastery of vocabulary proportion, etc.	19 (76%)	3	1
7. The interface design of the system is reasonable and beautiful, which can enhance learning interest and stimulate learning desire.	2 (8%)	8	2
The use of the system is of great help in memorizing vocabulary.	10 (40%)	9	0
For vocabulary learning, it is necessary for the system to recommend resources.	10 (40%)	5	0

This chapter mainly demonstrates the improvement of learning efficiency by the learning system proposed in this article through the comparison of learners before and after using the system for learning, as well as through interviews with learners. It also verifies the novelty of the improved learning design scheme.

Fig. 9 illustrates the comparison of the simulated distributions of scores and the learning gains for both the adaptive-system group and control group. As seen in the left panel of the figure, post-test scores of the adaptive group are gathered around a higher number compared to the control group. With the distribution being shifted toward the right, it tells that the learners who were engaged in the adaptive vocabulary acquired better vocabulary test results than those from the control group after the intervention. The dashed lines can represent the mean scores of the post-test and show how the two groups differ. For instance, in the right panel the distribution of the learning gain calculated for the adaptive group is also shifted rightward. The mean gain is around 20.0 points for

the adaptive group, while for the control group it is only 12.2 points. Hence, this means that both groups made a progress during the process, but the results of the adaptive system are a reflection of a greater progress compared to results of the control group. Moreover, the adaptive group displays a wider distribution of learning gains, which may show how people react differently to personalized offers.

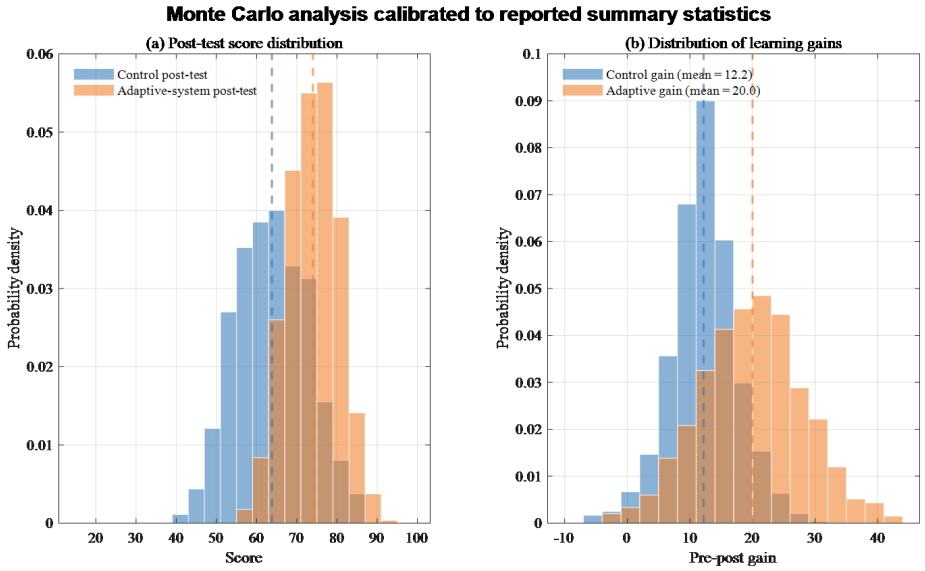


Fig. 9. Monte Carlo analysis calibrated to reported summary statistics

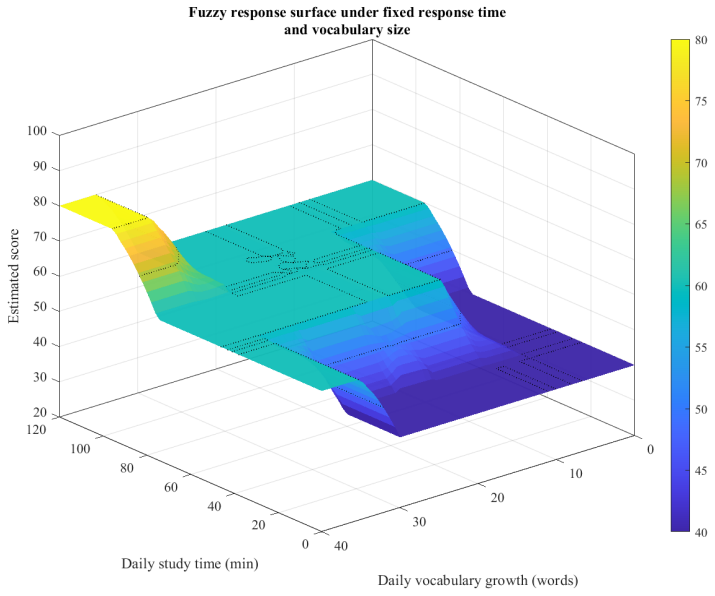


Fig. 10. Fuzzy response surface under fixed response time and vocabulary size

The three-dimensional response surface of the fuzzy inference model is shown in Fig. 10. A daily study time and daily vocabulary growth are used as two changed inputs, with average response time and total number of vocabulary learned remaining constant. Overall, the estimated score varies in the input space, indicating that the fuzzy model is capable of nonlinear mapping. When both variables are small, the predicted score

remains low. When vocabulary growth increases, the score rises proportionally, especially if the learner spends more time studying. The highest predicted score may be seen in the area where intensive study time and fast vocabulary growth take place. However, we can see that the surface is not flat and there are several plateaus and transition zones on it due to the application of overlapping membership functions and discrete linguistic rules. It illustrates that fuzzy inference works without sharp discontinuities, resulting from strict thresholds. A minor change in learner behavior leads to a smooth adjustment of the predicted score. Thus, the response surface demonstrates how efficiently a system can work with vague learner characteristics and produce well-grounded recommendations.

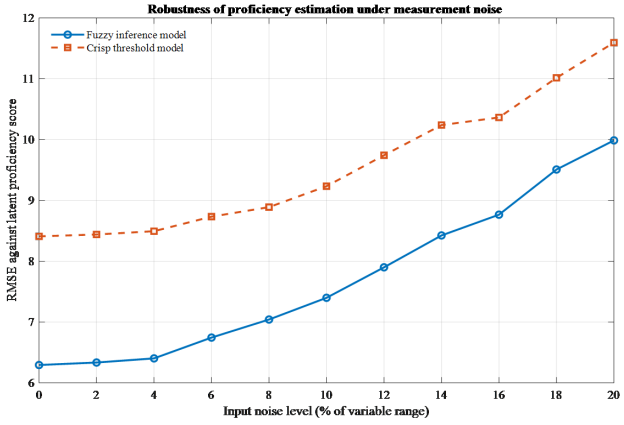


Fig. 11. Robustness of proficiency estimation under measurement noise

Fig. 11 measures the validity of the fuzzy inference system as the noise takes on greater values. The horizontal axis shows the degree of noise, which is expressed in the percentage of the range of four input estimates, while the vertical axis depicts the root mean square error with respect to the latent proficiency score. It appears that the error of the two models grows along with the uncertainty of the data. However, the fuzzy system maintains lower error values for all levels of noise present in the measurements. At a noise value equal to zero, its error value is smaller than that of the crisp model, which suggests that the fuzzy method is capable of an even closer approximation of the continuous reference proficiency function. As the value of noise increases from 0% to 20%, the error value of the fuzzy model goes up from 6.3 to about 10.0 while that of the crisp model climbs from about 8.0 to 11.0.

6 Conclusion

This article proposes a learning system that is more efficient and user-friendly for learners, based on the characteristics of online and offline English vocabulary learning systems on the market. The design scheme of the adaptive and fuzzy recommendation English learning system is completed, and the implementation styles of each functional module are designed to ensure the rationality of vocabulary recommendation through fuzzy reasoning mechanism. Fuzzy reasoning is adaptively adjusted according to learners' learning habits and learning effects, and can recommend targeted learning plans. There is a phenomenon of "one size fits all" in the current English vocabulary market, where all learners are presented with the same vocabulary resources without considering the differences in learning methods, preferences, styles, and existing cognitive structures of different learners. Such resource presentation methods make it difficult for learners to easily choose what is suitable for themselves when facing learning content, often spending more time and cost on resource screening. This not only disperses learning attention, reduces learning persistence, but also cannot guarantee learning efficiency. This study uses fuzzy logic reasoning mechanism to infer and process the input data through daily learning time, daily vocabulary growth, total vocabulary mastered, and average time spent on solving problems. Obtain student

grades, Assess students' abilities, match English vocabulary, and keep vocabulary resources within learners' acceptable range. The application of fuzzy logic reduces the external and internal cognitive load of learners, ensures the on-demand allocation of learning resources, enables personalized learning, and provides a reference plan for future English and other language vocabulary learning.

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